Multi-Agent Control of Thermal Systems in Buildings

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ABSTRACT

In buildings, the thermal functions of heating, ventilation, air conditioning and domestic hot water production are often interdependent. Additionally, it is more and more complex to control them, given the increasing use of alternative energy sources, such as solar thermal collectors or heat pumps. In this work, we propose an approach allowing to design and optimize the control of thermal systems in the buildings, while improving flexibility and reusability. Consumer, producer, distributor and environmental agents are used to represent the building and its appliances. These agents' internal models allow them to compute the energy needs, energy resources and associated costs, and take into account the specificities of the thermal systems. Following this modeling step, a distributed mechanism automatically controls the system, by combining a multi-criteria selection, a local optimization and a distributed allocation of the available resources. This approach was used to control a compact unit providing heating, ventilation and domestic hot water production in a low-energy building. The system was evaluated using a thermal simulator, and managed to improve the thermal comfort by 35 % compared to the initial control system, for only a 2.5 % increase in costs.

Categories and Subject Descriptors

I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence; J.2 [**Computer Applications**]: Physical Sciences and Engineering

General Terms

Algorithms, Design, Experimentation

Keywords

Multi-agent system, control, building, energy efficiency, domestic hot water production, heating, cooling

1. INTRODUCTION

Buildings represent an important part of the global energy consumption (e.g. 43 % in France [2]), and optimizing this consumption is, therefore, a major issue in the current energy challenge. To decrease the energy needs, the thermal functions in buildings are increasingly based on alternative energy solutions, such as solar thermal collectors, heat pumps or heat recovery ventilation. However, the diversity of these solutions and their interdependence lead to an increased complexity in the design of the control systems.

The optimization of the energy consumption in buildings has been widely studied [1, 5, 9, 14]. However, in most of the existing approaches, no other energy forms than electricity has been considered, nor the specificities they imply. For instance, when the energy is turned into heat and transferred through a fluid (gas or liquid), the distribution costs are not negligible – due to losses and power consumption of ventilators or pumps – and the energy transfers are restricted to connections through pipes or air ducts. Other works have focused on systems where the energy was transferred as heat, like in district heating systems [6, 16]. However, such approaches focuses how to control the demand, and not on how to integrate alternative energy sources. Recent works [13] have taken such sources into account, considering for instance the use of heat pumps. In this case, though, the control of more complex systems and the cost of energy distribution cannot be easily taken into account.

To address these issues, we propose an approach to design and optimize the control of the energy systems in buildings, which focuses on the thermal systems: heating, ventilation, air conditioning and domestic hot water production. The approach is based on the description of the building as a multi-agent system, combined with a distributed decision mechanism that is able to automatically control the building. The approach is flexible – a device can be easily added or removed, without having to redesign the whole control system –, and reusable – an agent designed for a specific system can easily be reused in another one.

In more details, this work advances the state of the art in the following ways:

- We present a novel architecture that allows to take into account the specificities of alternative energy sources and explicitly represents the energy distribution network, which allows to handle distribution constraints and costs. Adapted from supply chain management approaches [8] and from previous works in energy applications [16], the architecture is based on four agents types: consumer, producer, distributor and environmental agents. Their internal models are used to compute their needs and resources.

- We propose a generic mechanism to automatically control a system modeled using the above description. The mechanism is linked to the building by the representation of the real sensors and actuators, and combines a multi-criteria selection of the resources, a local optimization and a distributed allocation. It enables to optimize the building operation using different criteria, such as the energy consumption, the operating cost, or the environmental cost.

- Finally, we apply the approach to design the control system of a compact unit providing heating, ventilation and domestic hot water production in a low-energy building. Evaluated by a thermal simulator [15], the control system managed to improve the thermal comfort by 35 % compared to the initial control, with only a 2.5 % increase in costs. The approach will soon be tested on a physical test bench for final validation.

The remaining of the paper is organized as follows. In Section 2, we present the related works, and Section 3 gives an overview of the approach. Section 4 details the proposed architecture, and Section 5 presents the automated mechanism that controls the building thermal systems. In Section 6, the application of the model to a real device is described, as well as the obtained results. Finally, Section 7 presents the future works, and Section 8 concludes.

2. RELATED WORKS

The optimization of buildings energy consumption has been widely studied, and multi-agent systems are now well recognized for such applications [7]. For instance, Abras et al. [1] have proposed a building control system based on a multi-agent architecture, using a two level mechanism: a reactive level controls the building, and an anticipative level computes a long term plan. However, the approach is restricted to electrical systems, and does not improve the results of previous solutions. Other approaches take into account the inhabitants' behaviors [5] or the building architecture [14] to improve the energy consumption. However, none of them allow to take into account the specificities introduced by using an energy form other than electricity.

Such constraints have been considered in [16, 6], where the authors investigate the use of multi-agent systems to control district heating systems. Their objective is the minimization of the energy consumption and respect of the clients' comfort. The approach takes into account the specific constraints of hydraulic networks, such as delayed production time and thermal inertia. However, it focuses on demand control and does not allow for an easy integration of alternative energy sources, as it does not take into account the thermal specificities of each sub-system.

Finally, recent works have addressed the issue of integrating alternative heating systems, such as heat pumps [13]. Using a model of the thermal properties of the building and weather forecast, the approach enables to optimize the costs or carbon emissions of the building. However, more complex sub-systems cannot be easily introduced, and the approach does not consider the specificities of energy distribution and associated costs.

3. OVERVIEW OF THE APPROACH

In this section, we first present the context, before describing the objectives and giving an overview of the approach.

3.1 Context

Our main application field is the control of thermal systems in buildings, focusing in particular on heating, ventilation, air conditioning and domestic hot water production. Today, the systems installed in buildings often combine different devices:

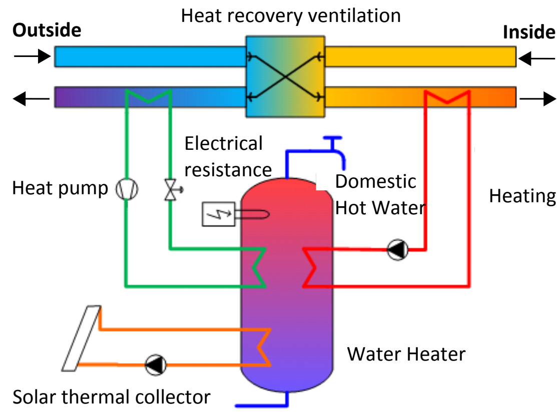


Figure 1: Simplified diagram of a system providing heating, ventilation and domestic hot water production in a building

- one or more heat pumps, that can be used for domestic hot water production, heating and/or cooling,
- a heat recovery ventilation, allowing to recover heat between the building incoming and outgoing air flows,
- a water heater, that can combine different heat sources: for instance, a solar thermal collector in the bottom part, an alternative source in the middle part, and an electrical resistance in the top part. The water heater can handle the domestic hot water production, and also contribute to the building heating through specific heat exchangers,
- other alternative energy sources, such as pellet stoves or geothermal heating, used directly or in combination with a water tank,
- energy storage solutions, through thermal storage in dedicated tanks, or geothermal storage.

In such systems, the devices often simultaneously handle different functions, which makes their control more complex. For instance, Figure 1 presents the simplified diagram of a system using some of these devices, and where the heat pump handles both domestic hot water production and heating, through the water heater.

In low-energy buildings, companies have developed specific systems, that handle various functions using a single compact unit [3, 11]. The proposed approach can be applied to design the control of such devices. It can also be applied to combined solar systems, or more generally to any system involving thermal control issues.

3.2 Objectives and Constraints

Engineers that develop the control of such systems face more and more complex issues. This work therefore targeted different objectives:

1. First, allow the use of different optimization criteria. In most approaches, only the global energy consumption is considered. However, with the introduction of alternative energies, other criteria become particularly interesting, such as the operating cost or the environmental cost.

2. Second, take into account the specificities of alternative energy sources, like heat pumps, which performances vary highly depending on environmental conditions.

3. Third, take into account the specificities of energy transfers as heat, through fluids or air: in such cases, the energy can only be transferred between physically connected points, and the transport auxiliaries – such as ventilators or circulators – have a non-negligible cost. For instance, in low-energy buildings, they account for 14 to 30 % of the total energy consumption.

4. Finally, ease the designer tasks: control systems are currently hardly reusable, because each development is specific to a particular system. However, the global management and the devices models are often similar, and could be reused between systems.

One of the objectives of this work was to develop a control system that would be embedded on an existing industrial system. This led to different constraints. First, the sensors had to be limited to those already present in the system. These sensors are few: on a compact unit for instance, only ten or so temperature sensors are used. Furthermore, the control system had to guaranty that the inhabitants' comfort would be respected, with the same level as previous solutions. Indeed, the system controls the heating, the ventilation and the domestic hot water production: it is not only unacceptable if any of these functions fails, but some of them are also constrained by legal regulations.

3.3 Description of the Approach

We consider systems including a set of appliances – that consume, produce or distribute energy –, a set of sensors, and a set of actuators. The objective of the control system is to compute, at each time step, the values that will be assigned to each actuator at the next time step.

The proposed method combines a modeling step, where the physical system is described as a multi-agent system, and a mechanism that automatically handles the control of the physical system, based on the previous description. Different agents types compose the multi-agent system (Fig. 2):

- *producer* agents represent the elements which purpose is to produce thermal energy,
- *consumer* agents represent the elements which handle comfort functions using thermal energy,
- *distributor* agents represent the elements which impact the thermal energy transfer: a *distributor* represents a subpart of the physical distribution network. It is associated to a set of *clients* – *consumer* agents or other *distributors* – and to a set of *suppliers* – *producer* agents or other *distributors*,
- finally, *environmental* agents provide additional information on the system physical environment.

This description leads to a hierarchical representation of the physical system: the *producers* are connected to the *consumers* through a hierarchy of *distributors,* that represents the energy distribution network.

Based on this representation, the control system runs as following. Using the observations available from the sensors

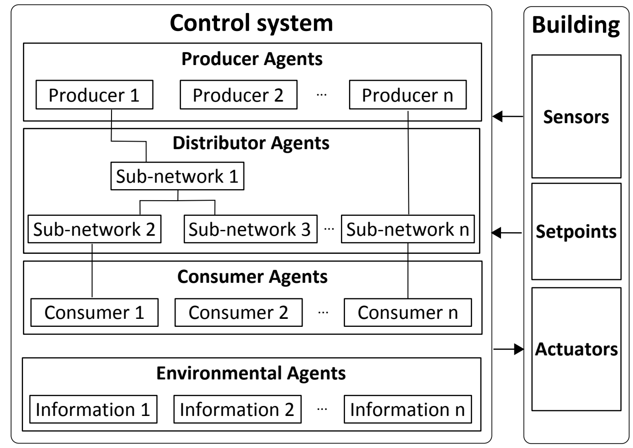


Figure 2: Overview of the system architecture

in the physical system, the agents build plans of their energy needs and resources. Through the *distributors*, a distributed optimization combines a multi-criteria selection and a local optimization of the resources between the *distributors* and their *suppliers*, before allocating the resources to the *clients*. When this step is completed, *producer*, *consumer* and *distributor* agents all have a plan of the resources they will receive and/or have to provide. These plans represent a determined state of all the system actuators.

Finally, the values of the actuators in the multi-agent system are assigned to the physical actuators, which controls the system.

This description and mechanism answer our different objectives. First, the explicit representation of the distribution network enables to take into account the costs and constraints it induces. Then, the agents embed internal models that allow them to compute their decisions using their internal (thermal) constraints. Moreover, the optimization step allows for the taking into account of various criteria. Finally, the agent based description increases the system flexibility, as replacing an agent does not influences the system modeling or the control strategy.

4. DESCRIPTION OF THE AGENTS

We now present the architecture of the multi-agent system used to model the building and its sub-systems. We define four kinds of agents: *producer* agents $a_p \in \mathcal{A}_p$, *consumer* agents $a_c \in \mathcal{A}_c$, *distributor* agents $a_d \in \mathcal{A}_d$, and *environmental* agents $a_e \in \mathcal{A}_e$. We have $\mathcal{A} = \mathcal{A}_p \cup \mathcal{A}_c \cup \mathcal{A}_d \cup \mathcal{A}_e$.

The duration between two control time steps is denoted Δt. $n = h_p/\Delta t$ is the number of forecast values (with h_p the forecast duration), $m = h_h/\Delta t$ is the number of history values (h_h the history duration).

We first introduce the notion of *device* $d \in \mathcal{D}$. A *device* represents information that could be associated to a real sensor or actuator, a cost, or a virtual sensor. A *device* includes an internal model used to update its forecast.

DEFINITION 1. *A* device d *is defined by:*

- *a value* v_d
- *an internal model* $\mathcal{M}_d$
- *a forecast* $P_d = (v^p_{d,i})_{1 \leq i \leq n}$

- *an history* $H_d = (v^h_{d,i})_{1 \leq i \leq m}$

Example 1. *Suppose we wish to represent the price of electricity from the electricity network, and associate it to a forecast and history. We define a* device $d_{c_{elec}}$ *that will hold these information.*

Among the set of *devices*, we distinguish the set $\mathcal{S} \subset \mathcal{D}$ of *sensors* and the set $\mathcal{B} \subset \mathcal{D}$ of *actuators*. A *sensor* is the software representation of a physical sensor, and an *actuator* is the representation of a physical actuator. These elements enable to interface the control system with the real system.

Example 2. *Suppose that a temperature sensor measures the internal temperature of the building. This physical sensor can be represented in the multi-agent system by a software* sensor $s_1 \in \mathcal{S}$.

A *producer* agent $a_p \in \mathcal{A}_p$ is an agent which purpose is to produce thermal energy. It holds an internal model $\mathcal{M}_{a_p}$ that allows to compute the energy resources e_p it can produce and the energy e_c consumed for this production. A *producer* also holds a set of *devices*, and it is responsible for their update. Among these *devices*, there could be *sensors* and *actuators*.

Definition 2. *A* producer *agent* a_p *is defined by:*

- *an internal model* $\mathcal{M}_{a_p} : (t_{start},\, t_{end},\, \mathcal{D}) \rightarrow (e_p,\, e_c)$
- *a set of* devices $\mathcal{D}_{a_p} = \{d_i,\, d_i \in \mathcal{D}\}$

Example 3. *For instance, a heat pump can be represented by a* producer *agent. It could update the* actuator *that controls its start, and be associated to the* sensors *that measure the temperature* T_{evap} *at its evaporator and the temperature* T_{cond} *at its condenser. Its internal model could for instance describe the energy produced depending on* T_{evap} *and* T_{cond}*:*

$$e_p = (a \cdot T_{evap} + b \cdot T_{evap}^2 + c \cdot T_{cond} + d) \cdot \Delta t$$

with a*,* b*,* c *and* d *characteristic values of the heat pump. The energy consumed for this production (here, electricity), could be given by* $e_c = P_{max} \cdot \Delta t$*, with* P_{max} *the compressor maximal power.*

A *consumer* agent $a_c \in \mathcal{A}_c$ is an agent which performs a comfort function using thermal energy. A *consumer* is associated to an objective function o_{a_c}, for instance a setpoint. It also holds an utility function u_{a_c}, which can be used to evaluate the respect of the objective function. This utility function can be a simple one, for instance taking into account the respect or not of the objective, or a more complex one, for instance varying dynamically depending on the respect of the objective. A *consumer* agent also holds an internal model $\mathcal{M}_{a_c}$, that allows to compute the energy needed to satisfy its objective function. Finally, it holds a set of *devices* that could be *sensors*, but no *actuators*.

Definition 3. *A* consumer *agent* a_c *is defined by:*

- *an objective function* o_{a_c}
- *a utility function* u_{a_c}
- *an internal model* $\mathcal{M}_{a_c} : (t_{start},\, t_{end}\, \mathcal{D}) \rightarrow e_b$
- *a set of* devices $\mathcal{D}_{a_c} = \{d_i,\, d_i \in \mathcal{D} - \mathcal{B}\}$

Example 4. *For instance, the thermal comfort in the building can be represented by a* consumer *agent. The objective function could be to maintain a fixed setpoint* T_{cons} *at 19°C, and its internal model could represent a thermal model of the building, allowing to compute the energy required to reach the setpoint, such as:*

$$e_b = C_b \cdot (T_{cons} - T_{int}) + UA \cdot \left(\frac{3}{2} \cdot T_{int} - \frac{T_{cons}}{2} - T_{ext} \right) \cdot \Delta t$$

with C_b *the building heat capacity (in J/K), and* UA *the building losses coefficient (in W/K).*

A *distributor* agent $a_d \in \mathcal{A}_d$ is an agent which function is to impact the energy transfers in the building. A *distributor* represents a subpart of the distribution network: the set of *distributors* represents the whole network of connections between appliances. A *distributor* holds an internal model, that allows to take into account the constraints and costs associated to the energy distribution, such as heat losses or the energy consumption of a ventilator. A *distributor* holds a set of *clients* – *consumer* agents or other *distributors*–, and a set of *suppliers* – *producer* agents or other *distributors*. By definition, a *producer* can only be the *supplier* of an unique *distributor*, and, similarly, a *consumer* can only be the *client* of an unique *distributor*. This definition leads to a hierarchical description of the system. Finally, a *distributor* holds a set of *devices* that could be *sensors* as well as *actuators*.

Definition 4. *A* distributor *agent* a_d *is defined by:*

- *an internal model* $\mathcal{M}_d : (t_{start},\, t_{end},\, \mathcal{D}) \rightarrow e_b$
- *a set of* clients $\mathcal{C}_{a_d} \subset \mathcal{A}_c \cup \mathcal{A}_d$ *with:*
  $\forall c \in \mathcal{C}_{a_d},\ c \in \mathcal{A}_c \Rightarrow (\nexists a_{d_1} \in \mathcal{A}_d - \{a_d\},\ c \in \mathcal{C}_{a_{d_1}})$
- *a set of* suppliers $\mathcal{F}_{a_d} \subset \mathcal{A}_d \cup \mathcal{A}_p$ *with:*
  $\forall f \in \mathcal{F}_{a_d},\ f \in \mathcal{A}_p \Rightarrow (\nexists a_{d_1} \in \mathcal{A}_d - \{a_d\},\ f \in \mathcal{F}_{a_{d_1}})$
- *a set of* devices $\mathcal{D}_{a_d} = \{d_i,\, d_i \in \mathcal{D}\}$

Example 5. *For instance, the heat distribution network between a solar thermal collector and a storage tank can be represented by a* distributor *agent. This agent will have one* supplier*, the solar thermal collector, and one* client*, the storage tank. The* distributor *can be associated to the* actuator *that circulates the fluid in the network. Its internal model could reflect the energy consumption induced by this distribution:*

$$e_b = P_{max} \cdot \gamma \cdot \Delta t$$

with P_{max} *the pump maximal power (in W) and* γ *the control signal between 0 and 1.*

Finally, an *environmental* agent represents complementary information on the environment of the physical system. These information are represented through *devices*. Among these *devices*, there could be *sensors*, but no *actuator*.

Definition 5. *An* environmental *agent* a_e *is defined by a set of* devices $\mathcal{D}_{a_e} = \{d_i,\, d_i \in \mathcal{D} - \mathcal{B}\}$

Example 6. *For instance, the cost of the electricity from the electricity network can be represented by an* environmental *agent* a_{elec}*, that would handles the update of a* device $d_{c_{elec}}$ *representing this cost.*

Each device is associated with an unique agent, that is in charge of its update: $\forall d \in \mathcal{D},\ \exists! a \in \mathcal{A},\ d \in \mathcal{D}_a$.

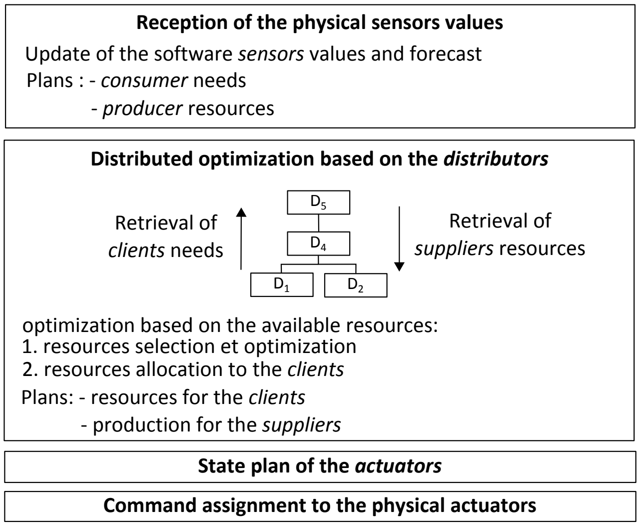


Figure 3: Main control loop

5. AUTOMATED CONTROL SYSTEM

This description of the physical system as a multi-agent system allows for the use of an automated control mechanism. In this section, we first present the main loop of the control system, before focusing on the optimization step.

5.1 Main Control Loop

The main loop of the control system handles all the operations executed at each time step, resulting in the control of the physical system. Figure 3 graphically presents the different stages involved.

The time step begins with the reception of updated information from the physical system (i.e. updated sensors values). The initial value of each of the *sensor* is updated using the value measured by the corresponding physical sensor. Then, each agent $a \in \mathcal{A}$ computes the forecast of the *sensors* it is in charge of, using the *sensor* internal model.

Using its internal model, each *consumer* agent then builds a plan describing its energy needs, and the corresponding utility. Similarly, each *producer* agent builds a plan describing the resources it is able to produce, and the associated costs. Based on these data, a distributed optimization step takes place, based on the *distributors*. This step, further detailed in Section 5.2, combines different algorithms allowing to select, optimize, and allocate the resources according to the chosen criteria. This step builds for each *producer*, *consumer* and *distributor* agent a plan of the resources they will receive and/or have to provide. Using the *actuators* internal models, these plan are converted to a determined state of all the *actuators* in the system.

The *actuators* values for the next step are then assigned to the physical system actuators, which controls the system.

5.2 Distributed Optimization

The distributed optimization step is based on the *distributor* agents. The objective of this step is to maximize the chosen criteria, while taking into account the specificities of the physical system. For instance, when low cost resources are available, such as heat produced by a solar thermal collector, they have to be used before more expensive resources, such as those produced by an electrical resistance. Moreover, the mechanism has to anticipate the production of the resources, allowing for instance to wait before using the resistance if a solar production has been forecasted.

The proposed mechanism presents the following characteristics: it allows to select the cheapest (in terms of the chosen criteria) resources on the forecast duration; it allows to simultaneously optimize interdependent appliances (for instance, in Fig. 1, the heat pump performance depends on the internal temperature, the heat recovery ventilation performance, the air flow, and the water heater middle temperature, that all dynamically change over time); it allows to take into account the cost of the auxiliaries; and finally, it allows to respect the inhabitants' comfort specifications.

To build this mechanism, we combined resources selection, resources optimization, and resources allocation algorithms. The mechanism runs as follows. At each time step, a *distributor* first retrieves the needs of each of its *clients*. When all the information have been received, it updates its own needs plan, consolidating the data from its *clients* and computing a local utility. This consolidation is done by adding the needs of each *client* and the additional cost introduced by the *distributor*, computed using its internal model:

$$\forall i \in [1,\, n],\ e(i) = \sum_{c \in \mathcal{C}_{a_d}} e_b(c, i) + \mathcal{M}_{a_d}(t_i,\, t_i + \Delta t,\, \mathcal{D})$$

The utility associated to each of these needs is the maximum of the *clients* utilities at this time step. This plan is then available for the *suppliers* of the *distributor*, allowing for an automated hierarchical update of the plans. Similarly, the *distributor* retrieves the resources plan from its *suppliers*.

The objective is then to select, among the available resources, those which optimize the chosen criteria, while meeting the *clients* needs. To do so, the following process is used:

1. if the global needs are not covered by the total set of available resources, we select all of them and compute the resource allocation phase. If not, we go to step 2,

2. the *distributor* and its *suppliers* compute a local optimization of the resources, that allows to take into account the effect of energy distribution on energy production. Using their internal models, they converge on a solution maximizing their performance, but that could not satisfy the *clients* needs. If the obtained resources cover the needs, we compute the resource allocation. If not, we go to step 3,

3. to obtain a set of resources as close as possible of the needs, we start from the initial resources set of step 1, and progressively increase the performance of each pair of *distributor* and *supplier* (increasing the performance decreases the size of the available resources), until the set of resources is as close as possible from the needs.

At the end of this phase, the plan of the *distributor* holds the selected resources, which have been optimized with its *suppliers*. The next phase it to allocate these resources to its *clients*. For each time step of the plan, the selected resources are attributed depending on their utility and needs.

According to the results presented in [12], we chose to use flexible and social agents' behaviors, to achieve the most efficient result. This allocation builds a production plan for each *supplier* of the *distributor*, and a *supplier* plan for

Sensors	T_{wtt}	Storage tank temperature (top)
	T_{wtm}	Storage tank temperature (middle)
	T_{wtb}	Storage tank temperature (bottom)
	T_{sol}	Solar thermal collector temperature
	T_{ext}	External temperature
	T_{int}	Building temperature
	T_{old}	Outgoing air temperature
	T_{new}	Incoming air temperature
Actuators	c_{hp}	Heat pump (stop, start)
	c_{sol}	Solar pump (between [0, 1])
	c_{res}	Electrical resistance (stop, start)
	c_{vent}	Ventilator (between [0, 1])
	c_{heat}	Heating pump (between [0, 1])

Table 1: Sensors and actuators of the device

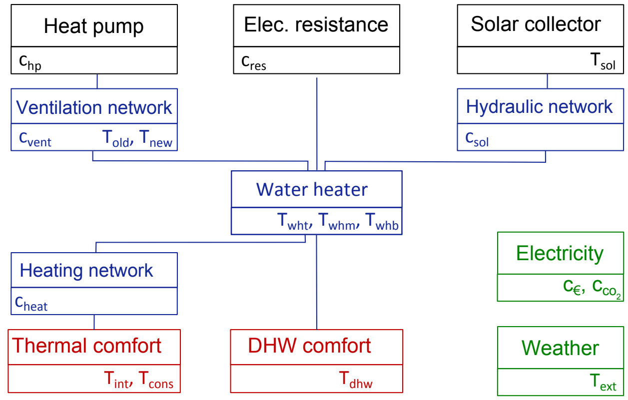


Figure 4: Modeling of the system using the proposed architecture

each of its *clients*. The hierarchical description of the system guaranties the convergence of the mechanism. Here, we suppose that all agents can be trusted, and that they answer to all information requests. Indeed, since the goal is to provide a mechanism able to produce results as good as existing solutions, we do not take into account these possibilities, which could be added in future versions.

At the end of the process, the *distributors* and the *producers* have all an updated production plan, and the final step of the main control loop can be successfully executed, leading to the control of the system.

An important advantage of this process is that it is fully automated, once the agents have been defined. In particular, specific rules for each appliance do not have to be defined, and the mechanism automatically adapts to modifications in the agents organization.

6. APPLICATION

In this section, we present the application of the proposed approach to a compact unit that provides heating, ventilation and domestic hot water in a low-energy building. We first describe the modeling of the system, before presenting experimental results.

6.1 System Modeling

The objective was to design the control system of a compact unit similar to the one introduced in Sect. 3.1, Fig. 1. The available sensors and actuators are described in Table 1.

The unit combines a heat recovery ventilation, a storage tank, a heat pump, a solar thermal collector and a heating electrical resistance. We model these elements as follows (Fig. 4): the heat pump, the solar thermal collector and the electrical resistance are *producer* agents; the thermal and domestic hot water comfort are *consumer* agents.

We use the heat pump internal model presented in Example 3. For the electrical resistance, $e_p = e_c = P_{max} \cdot \Delta t$ (with P_{max} the resistance power in W), and, for the solar thermal collector (from standard [10]):

$$e_p = S \cdot G \cdot \left(\eta_0 - a_1 \cdot \frac{T_m - T_a}{G} - a_2 \cdot G \cdot \left(\frac{T_m - T_a}{G} \right)^2 \right) \cdot \Delta t$$

with S the collector surface (m^2), G the solar irradiation ($W.m^2$), η_0 the optical factor, a_1 and a_2 loss coefficients ($W.m^{-2}.K^{-1}$), T_m the collector mean temperature and T_a the external temperature (K). The collector does not consume energy, therefore $e_c = 0$.

The *consumer* agents represent comfort functions. The building thermal comfort is represented by a setpoint fixed at 19°C during the [0h, 10h] and [18h, 24h] periods of week days, at 16°C between 10h and 18h, and at 19°all days during weekends. The parameters C_b and UA of the building model were learned using a least squares method and a thermal simulator of the building [15]. The domestic hot water comfort is represented by a fixed 50°C setpoint at the top of the water heater, which reflects the comfort provided by existing systems.

The following *distributor* agents model the energy distribution network:

- an agent represents the ventilation network, including the ventilators and the heat recovery exchanger. It has one *client*, the storage tank, and one *supplier*, the heat pump. Its internal model represents the ventilators energy consumption:

$$e_b = P_{max} \cdot (a_0 + a_1 \cdot \gamma + a_2 \cdot \gamma^2) \cdot \Delta t$$

  with P_{max} the ventilator maximal power (W), a_0, a_1, a_2 characteristic values of the ventilator and γ the command between 0 and 1,

- an agent represents the hydraulic network between the solar thermal collector and the water heater. It has one *client*, the storage tank, and one *supplier*, the solar thermal collector. Its model is similar to the one described in Example 5,

- an agent represents the storage tank. It has two *clients*, the domestic hot water comfort and the heating network, and three *suppliers*, the ventilation network, the electrical resistance and the solar hydraulic network,

- finally, an agent represents the heating network between the storage tank and the building incoming airflow. It has one *client*, the thermal comfort, and one *supplier*, the water heater. It includes a pump, which model is similar to the one presented in Ex. 5.

Two *environmental* agents represent the system externalities: the first one represents the weather forecast, corresponding to the external temperature sensor; the second one provides the operating and environmental costs for the electricity coming from the electricity network.

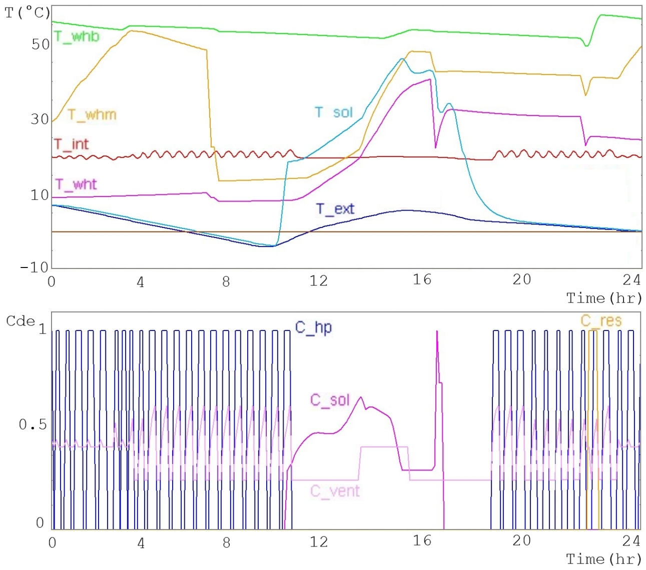


Figure 5: Sensors and actuators values of the compact unit controlled by the multi-agent system during a one day period, as measured in TRNSYS

The internal models for the *sensors* are based on persistence or historical models, except for the inbound and outbound airflows, which use the heat recovery exchanger performance factor. The *actuators* internal models represent the implementation of the production plan of the agents.

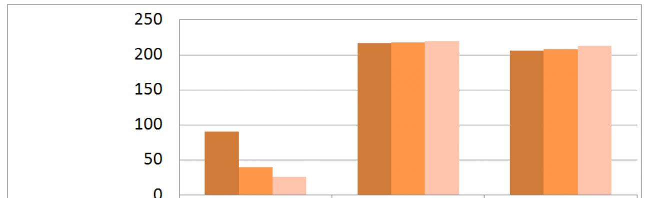
6.2 Experimental Results

The compact unit presented here represents an existing prototype. During the design of this prototype, power systems and control engineers have used a dedicated thermal simulation tool, TRNSYS [15], to design the system and its control. To validate the proposed approach, we compared its results with those of the existing control system.

To do so, the multi-agent system and TRNSYS were linked together: at each time step, TRNSYS computes the thermal simulation of the building and compact unit, and updates the sensor values; using these values, the multi-agent system computes the next actuators values, and sends them to TRNSYS; these values are then used by TRNSYS during the following time step. The multi-agent system was implemented in Java, using the interface of Repast to visualize results.

Figure 5 illustrates the obtained results. It represents the outputs of TRNSYS for a one day period. The first graphics represents the sensor values – for instance, the external temperature T_{ext} varies between -4°C and 6°C –, and the second one represents the actuators values. We observe oscillations of the heat pump command, corresponding to periods when heating is needed, with periodical freezing due to the environmental conditions. The heat pump uses a 6 minutes short cycle timer, but has to be stopped regularly to launch a defrost cycle. Between 10h and 18h, the setpoint decreases: heating is not needed any more, and the heat pump remains stopped. The variations of the ventilator command result from the optimization of the heat pump performance and the ventilation *distributor*.

To validate the interest of the approach, we compared the results of different control systems:



	Thermal comfort (hours of non-respect)	Electrical consumption (kWh/10 per year)	Cost (€ per year)
Basic control	90,5	216,2	205,5 €
Optimized control	39,5	217,6	207,7 €
Multi-agent control	25,8	219,1	212,9 €

Figure 6: Results of one year simulations of the compact unit operating in a low-energy building with different controls, using TRNSYS

1. a basic control system, based on reactive rules using temperature setpoints,

2. an optimized control, designed by power systems engineers to take into account the unit specificities. It includes in particular a mechanism to anticipate the heating needs, and a linear control of the actuators to optimize the energy transfers,

3. the multi-agent control system.

Figure 6 presents the results obtained with a one year simulation of the device in a low-energy house, using TRNSYS. The total duration of a one-year simulation is 9 minutes, using a control time step of 6 minutes. On a real system, the control time step is usually 1 minute (1 Hz vs the 160 Hz obtained here). The multi-agent control system increases the heating comfort by 35 % (-14h/year of discomfort) compared to the optimized control system. Compared with a basic regulation, the improvement is even higher: +71 %, 65h/year. Moreover, using the multi-agent control, the number of hours when high deviations from the setpoint occur (more than 1°C) decreases by a factor 2. As for the domestic hot water comfort, it is respected in all solutions.

When we consider the annual electrical consumption, the multi-agent control leads to a 0.7 % increase (+15 kWh/year) compared to the optimized control. A more detailed analysis shows that the ventilation consumption decreases by 4 %, when heating increases by 1 % and domestic hot water production by 3.3 %. Note that the optimization of the auxiliaries consumption that we observe here was not possible in previous control systems. However, the domestic hot water production increases its use of the electrical resistance, which leads to a global consumption increase.

Finally, the operating cost incurs a 2.5 % increase over the year when using the multi-agent control system (+5.2 euros). The cost of the ventilation and heating decreases by respectively -1.5 % and -2.8 %, but provides an improved heating comfort. However, the cost of the domestic hot water production significantly ponders the results, with a +19 % increase. Indeed, the current comfort function does not enable anticipations that could improve the energy consumption.

To conclude, the multi-agent control system managed to significantly improve the thermal comfort in the building, with a limited increase of the operating costs. Considering the additional value of the enhanced reusability and flexibility of the system, these results are very interesting. Moreover, the control patterns produced by the multi-agent control system are different of those obtained using state-of-the-art control techniques, which means that similar results could be achieved with very different strategies. This leads to consider future interesting complementary optimizations.

7. DISCUSSION AND FUTURE WORKS

As the first industrial application of the approach led us to implement it on a centralized automaton, the proposed approach was not evaluated in a distributed context. It would be interesting to do so, to increase the number of potential applications. We also consider extending the approach for home management systems, by handling electrical appliance as well as thermal ones.

Moreover, the approach was designed to be easily extended. Therefore, we plan to introduce new features, in particular regarding the prevision of the inhabitants' behaviors [9, 4]. Indeed, such models can easily be introduced using a combination of agents' internal models and *environmental* agents.

When we consider the thermal comfort function used in this paper, its objective is to maintain a specific temperature setpoint in the building. Indeed, one of our goals was to provide at least the same comfort level as the existing controllers, which use such a function. In future works, we plan to explore the use of more complex functions, which could lead to improve the trade-off between comfort and energy consumption.

Finally, at the application level, upcoming improvements include the evaluation of dynamic variations of the electricity prices, and the introduction of self-adaptation capabilities in the agents. The objective is to allow an autonomous adjustment of their internal models to the environment they are deployed in.

8. CONCLUSION

In this work, we proposed an approach to design and optimize the control of thermal systems in buildings, focusing on functions such as heating, ventilation, air conditioning and domestic hot water production. This approach combines a modeling step that describes the building as a multi-agent system, and a mechanism that automatically controls the building, based on this description.

The physical system combines sensors, actuators, and various devices, which are modeled as producer, consumer, distributor and environmental agents. Using the agents' internal models, the control mechanism determines their needs and resources. Then, it combines the selection, the optimization, and the allocation of the resources to optimize the chosen criteria. At the end of the process, the actuators state is fixed. To control the system, these values are assigned to the physical actuators.

We applied this approach to the control of a compact unit that provides heating, ventilation and domestic hot-water production in a low-energy building. The proposed approach managed to improve the previous control system results, leading to a 35 % increase of the thermal comfort, with a 2.5 % increase in costs. The approach will soon be evaluated on a physical test bench to validate these results in experimental conditions.

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