Self-Adaptive Energy Saver

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***Abstract*—Currently one of the main areas of improvement of the buildings energy performance is the optimization of regulation systems and controlling the flow of energy. To this end, we propose an approach based on multi-agent systems in which the optimization is performed without prior knowledge about the dynamics of the building. We evaluate the developed multi-agent system on its learning ability and optimization of the set point during the night. We show that the result converges efficiently towards the optimum, previously determined by a professional building simulator. This approach is generic enough to be extended to many observable and checkpoints building without modification of the algorithms decision agents.**

I. Introduction

In order to raise building energy performance two axes can be followed. The first one is to optimize the building itself using better isolation material and appropriate devices such as heat pump or solar panels. The second one is to improve regulation systems that schedule and command heating and cooling devices. This paper topic focus on this second approach.[1]

Building energy management is also a domain experiencing recent changes. Traditionally, energy follows a one way direction going from production points to customers through providers. This model is going to change with the development of devices able to produce energy such as solar panels or wind turbines. The pricing system is going to follow this development such that prices are not only dependent on the time of the day, but also on the consumer demand. [2] [3] Also, the electricity network is experiencing heavy fluctuation over time. It is well known that electricity demand hits periodical peaks early morning time or exceptional peaks during particularly hot summer or cold winter season. The energy takes into account those events by increasing dramatically the price of the energy when the consumer consumption is too high.

Those reasons lead us into research of new energy regulation method requiring to take into account both current states and future changes in the energy domain. Goals of regulation systems are to maintain the internal building climate in a comfortable state for the users need and to minimize the energy usage. The system described in this paper is designed to work without preliminary study of the building. It is able to learn and self-adapt to the dynamics of its environment without the help of any external resources such as an analytic model of the building nor a specific learning tool.

In section II, a domain analysis is presented in order to define the main domain constraints and their relations. The system SAVER, for Self-Adaptive Energy SavER, is then described followed by the behavior of the agent in the system ,in sectionIII. Sectiont IV presents two experiments on a simulated building on which we preliminary evaluate the optimal regulation set points with a space exploration. The SAVER system is then instanciated on this application and we compare the given solution to the optimal ones. Finally, sectionV presents a comparative analysis with the existing regulation methods applied in the building energy management.

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II. Domain Analysis

Our study focuses on the energy regulation in an office building. For this kind of building, we consider as inputs the set of controllable HVAC (heating, ventilation, and air conditioning) devices within the building. Sensors such as thermometers, presence detectors or energy meters constitute the outputs. Finally, three sets of constraints are expressed within the building.

- Firstly, building users wish to be in a comfortable environment for doing their tasks.
- Secondly, the building owner wishes to keep the energy usage cost at the lowest state but still satisfying users.
- Thirdly, energy producers and providers wish to limit regular energy demand peaks that occur every morning and evening.

A. The Dynamic

Office building are characterized by occupation patterns following work periods, as well as energy prices are higher during daytime than night time. The actual way building climate is regulated follows the office occupancy period. Indeed, the main regulation scheme currently applied is binary. The building regulator uses two set points. The first one during daytime, for instance 22°C, and the second one during night time, for instance 19°C or even completely shut down eating and cooling systems.

As a consequence, energy usage matches this pattern, leading to the situation where the energy is mainly consumed when the price is high, over a static periodic scheme. The claim of this paper is that the way energy is used, that is following a static day/night pattern, is far from optimal. An appropriate control system should be able to customize orders for each controllable heater and cooler in order to avoid consuming energy when the price is high as it also maintains a comfortable building climate.

B. Problem Definition

The problem to tackle is to minimize the energy usage while satisfying the comfort within the building. This is an

usual regulation problem under constraints. Figure 1 shows how the regulator perceives the building. A such problem is very general and is present in every building. Thermal dynamics are subject to changes due to, for instance, reorganization of the building or devices wear. The building occupancy is also subject to changes which lead to changes on the comfort constraint. The regulation system should be able to adapt to those unpredictable changes and to deliver in a short time a correct regulation function. Furthermore, the size of the building is not known before hand by the regulation system. The solution should then be generic enough to be reusable in a majority of buildings without involving human intervention for the tuning.

III. SAVER

In this section, we show how a multi-agent system fits our needs. The proposed system is then described in details.

A. Adaptive Multi-Agent System Theory

According to the problem definition, the solution we design must satisfy some requirements. We want to minimize the intervention of human when the solution is applied into a specific building. Then, the system must be adaptive to the building dynamic and autonomously learn it by itself.

In a multi-agent system based on the AMAS theory, each agent acts according to local information it can perceive and does not rely on the knowledge of universal information such as the overall goal of the system. Only local cooperation rules between agents are defined in order to guide the action of the agents in the system. The global system behavior is then not determined at the system design step, we call it emergent as it is the result function of all the interactions between the agents. This conception allows the system to always self-adapt to its environment as showed in [4] and [5].

Moreover, regulation mechanism based on the AMAS theory [6] shows the validity of the approach. In the context of energy regulation, we dispose of a limited amount of information on the buildings in which SAVER will be used and we proposea system called SAVE, based on the AMAS theory. We specify the local interaction rules between agents in order to obtain the appropriate regulation function in an emergent manner.

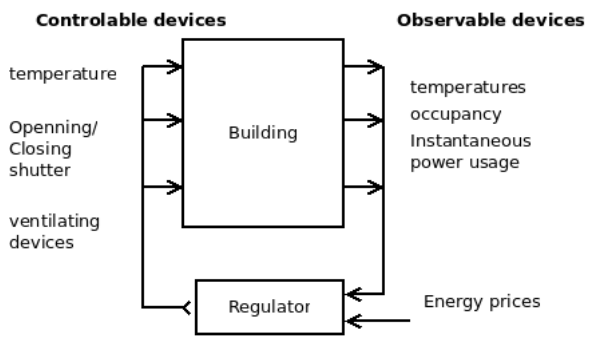

Fig. 1: The building seen by its regulator

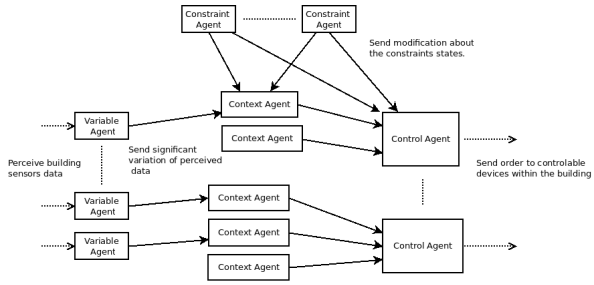

Fig. 2: Saver design

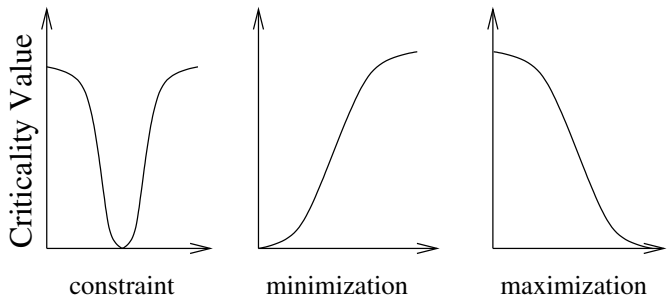

Fig. 3: Tree forms of criticality functions

B. Agents of the System

The conception of the SAVER system is made in order to obtain a generic ability to regulate the energy within a building.

It is constituted by four types of agents as showed in the figure 2.

1) Variable Agent: Variables agents map in the system each sensor of the building. Its role is to transmit to the other agents the value given by the sensor it is associated to. This transmission is implemented in the system by a method of message passing with the following constraint: a Variable agent is initialized with a predefined accuracy which is used by the agent as a threshold in order to limit the amount of messages the agent can send. For instance, an accuracy of 1°C given to a Variable agent associated to a thermometer will enable it to send messages only if the temperature variation is equal at least one degree from the last time a message has been sent. The state of a Variable agent stands for the knowledge the other agents have of it and is the last value sent by the agent.

2) Constraint Agent: Constraint agents represent requirements the system should consider. They are initialized with the knowledge of existing Variable Agent, potentially multiple, plus a function. This function calculates its criticality from the state of the Variable agent.

Figure 3 shows different forms of criticality function when the Constraint agent uses only one Variable agent state to define its criticality. We can see that by changing its criticality function, a Constraint agent can be seen as a constraint to satisfy, such as keeping a sensors value near a given set point, or an optimization we wish to perform such as minimization or maximization.

When we wish the system to enforce a particular desire, such as maintaining room temperature or keeping energy flow

within an electric line as low as possible, then a constraint agent has to be defined.

3) Action Agent: In the same way Variable agents map sensors, Action agents map controllable devices inside the system. It has the ability to send orders to a concrete device in the form of set points. They are also initialized with some information such as the allowed range of set point a device can accept, an accuracy and an initial set point.

Action agents observe every Constraints agents state. It is responsible to take a decision, at any time, on the set point it gives to its associated device in order to minimize Constraints agents criticalities.

However, at the start of the system, Action agents do not have predefined ideas about the role of the device within the building. In other words, at the start of the system, the Action agent doesn't know whether its action will have beneficial effect on constraints agents criticalities or not. The effect of its decisions should then be learned and eventually modified in order to minimize contraints agents criticalities.

It seems obvious that this procedure is rather complex and hard to write at the design step. That is the reason why we introduce the next agent that will help the Action agent to take its decisions.

4) Context Agent: Context agents are associated with a specific Action agent. The assumption we do for designing the system is that the effect of the controllable devices on the building are reproducible. It means that, for a particular state of the building, which is a combination of states of each Variable agent, a specific order given to a device nearly always leads the building to the same state.

With this assumption, the Context agent keeps a record of the action taken by its Action agents during a specific state of the building. Later, when the building enters the same state, the Context agent will be able to remind several information to the Action agents such as: the previously given order and the effects of it on the constraints criticalities.

C. Detailed Behavior

In this section we detail Context and Action agents behaviors as they are the two main agents in the system.

1) Context Agent Knowledge and Behavior:

a) Order Definition: The Context agent owns an order that its Action agent could apply. The order is a numerical value in a range defined by the user and given to its associated Action agent.

b) Forecast Definition: A Context agent should memorize the effect of an order on the controlled system in order to give it to the Action agent when the context will be observed again. The information needed by the Action agent is essentially the effect of the order on the constraints. Because it is the goal of the Action agent to minimize constraints.

The Context agent then stores the evolution of each constraint after the application of the proposed actions with a single numeric value for each constraint. This value is defined as the relative variations of the constraint during the period of application of the order proposed by the Context agent.

c) Context Definition: The Context agent observes every variable agents state. For each of them, the agent owns a range composed of two bounds: a minimum and a maximum.

When a Context agent can observe every variable state within its ranges, it can deduce that the current state of the building is the one the Context agent works on. The Context agent is then named as Valid. Otherwise, if any variable is not within its ranges, the Context agent is Invalid.

2) Action Agent Knowledge and Behavior: An Action agent observes its associated Context agents in a Valid State. In other words, an Action agent only focuses on Context agents that have information about the current state of the building.

The Action agent should pick an order among the offered proposition of the Valid Context agent pool. The following rule is applied at this step.

a) Cooperative Rule of Selection: From the Action agent point of view, a cooperative choice would be to focus on the most critical constraint and being sure to not lead the others in a critical level over the expected value for the chosen one. The Action agent applies this rule by sorting the proposed order by comparing the expected criticality value for every constraint and not the most critical only. Then, it chooses the action that lowers the maximum of the expected criticality value within constraints.

IV. Results

In this section, we present the results achieved by applying the SAVER system on the regulation of a simulated building's climate during the night. Various experiments are made on a simulated testbed in order to show how the SAVER system learns and adjusts itself. The building energy simulation tool TRNsys [7] is used for designing the building and simulating its behavior.

In a first step, we preliminary study the set of possible regulation solutions in order to get the optimal solution. Then, in a second step we execute SAVER on the same building without giving it any knowledge of the building structure or thermal properties. Finally, the solution given by SAVER is compared to the optimal solution we found in the first step, which enables us to conclude on its learning and control abilities.

A. Simulated Building Description

The model used as a testbed is a single room building simulated during a period of two winter months. Each zone is a room equipped with a controllable electric heater from which we can measure the instantaneous power used.

The price of the energy is calculated using the standard pricing scheme of the French electricity provider: 7.9 cent€/Watt between 6 AM and 10 PM ; 11.5 cent€/Watt otherwise.

In each zone, we put a thermometer in order to evaluate the difference between the order given to the heater and the actual temperature within the room. Human behavior is not simulated, however we evaluate the comfort in each zone during the occupation plan by the absolute difference between a standard comfort temperature, 22°C and the actual temperature of each

Night time temperature	Optimal set point
0°C	14.5°C
5°C	16.5°C
10°C	18.5°C
15°C	19°C

TABLE I: Optimal set point that minimize energy and satisfy comfort

zone. Finally, the weather is simulated using real data recorded from a station located in Paris.

In this model, we have one input point which is the heater, and a total of 3 output points, that is to say the inside thermometer, the outside temperature and the time of the day. We desire to make the building comfortable during work period which means the following constraint to satisfy: we want the temperature to be as near as possible to the comfort temperature. The total energy price at the end of the simulation is our optimization criteria.

B. Optimal Solution

The problem tackled is to find for every night of the simulation which set point the heater should maintain in order to satisfy the comfort constraint while minimizing the energy usage.

We can see that the building internal temperature and the energy usage only depend on two factors: the external temperature which is not controllable and the set point chosen for a night.

We make a sampling of the possible set of points for a night in 4 different outside conditions. We actually try for each night various set points from 12°C to 22°C with a step of 0.5°C.

The sampling is represented on the horizontal axis of the figure 4 while the vertical axis shows the energy used in order to maintain the comfort constraint.

Each curve shows the energy used according to different night time set points and outside temperatures. The minimum of each curve indicates the optimal set point that minimizes the energy usage while satisfying the comfort constraint. They are summarized in the table I.

We can now conclude that there is a specific optimal set point for each night that depends on the outside temperature. We also conclude that the outside temperature is a relevant information that the SAVER system can use in order to adapt itself and adjust its outputs.

C. Saver Instanciation

For the following experiment, the SAVER system is initialized with one input variable that follows the outside temperature and one output point that controls the set point for the heater. The goal of the system is to find for each day the optimal set point for the heater during the night. This is introduced in the system with a Constraint Agent that uses a minimization criticality function on the energy usage measure. The figure 5 shows the SAVER system instantiated with one Variable agent on the input point, one Action agent on the night time set point control point and the Constraint agent.

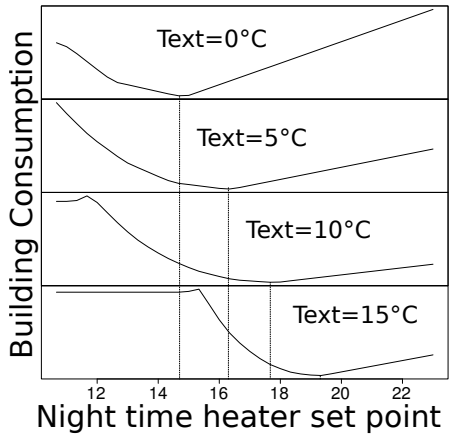

Fig. 4: Building energy consumption versus night time set point

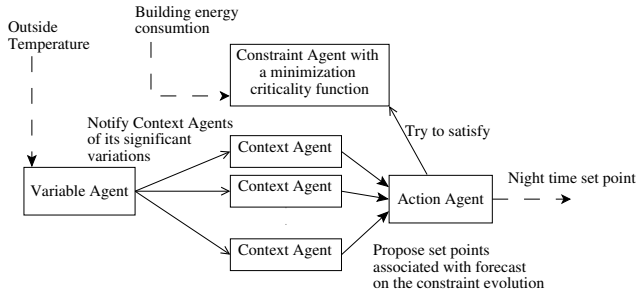

Fig. 5: Saver instantiated with one input point, one output point and a constraint

Context agents are created at runtime according to the evolution of the Variable Agent, their number is then not known before hand.

D. Convergence to the Optimal Set Point

One of the main issue when dealing with optimization is that we wish to obtain the optimal solution and avoid to stay

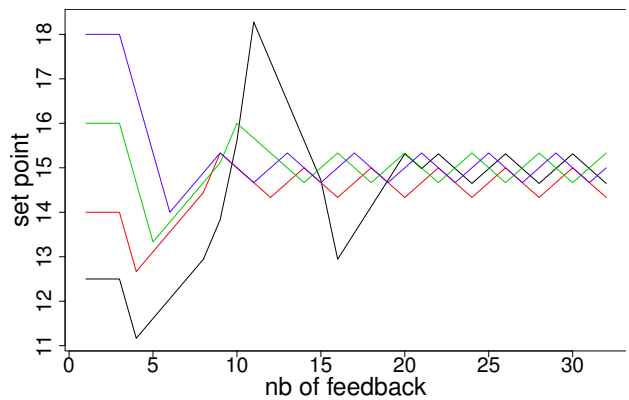

Fig. 6: Saver converging to different optimums according to external temperature

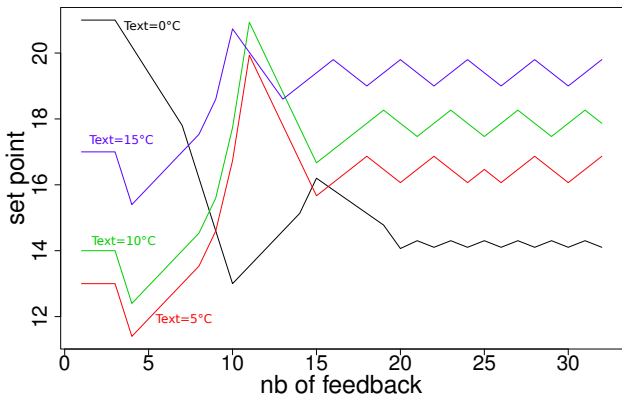

Fig. 7: Saver converging to the optimum for Text=5°C with different initialization points

in local optima. We have made some experiments in order to evaluate the convergence of the system into an optimal solution. Figure 6 shows a sample of 4 experiments in the situation where the external temperature of the building is 0°C. The abscisse represents the learning step of the system and the ordinate represents the set point given by the Action agent. The 4 curves show how the SAVER system converges to a stable set point from a different initialization point.

We observe that the system converges always to the same set point solution, which is the optimal solution found in table I in the case of 0°C outside. Moreover, the number of learning steps required by the SAVER system to converge from those initial situation are similar. This experiment shows the independence of the system against its initial state, as its robustness.

Finally, the set point oscillations observed after the convergence are due to the adjustment mechanism within the agents that is still on-going. This guaranties that the SAVER system keeps self-adapting to the dynamic of the building, (even to the slightest changes) and will always deliver in few adjustment steps the optimal solution.

E. Convergence for External Temperature

Figure 7 shows the solution found by SAVER for different external temperatures. The graph labels are the same as for figure 6. We can observe that SAVER converges in the same manner as in the previous experiment, that is with a number of learning steps limited to 20. Moreover, final set points for each outside temperature cases are the same as the one previously found in the table I.

V. Related Work

In this section, we look over the main control approach used in the building energy management.

A. PID : Proportional, Integrate, Derivative

A PID is a closed loop controller based on the comparison between the output of the system and the user given order. Figure 8 shows an overview of the closed loop. The calculated error ε is then used in order to calculate the actual command given to the system following a weighted sum of three factors:

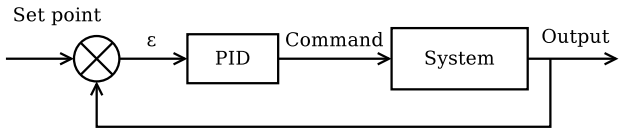

Fig. 8: PID control closed loop

- ε weighted by the proportional factor P,
- the variation of ε over the time weighted by the derivative factor D,
- the accumulation of ε over the time weighted by the Integrate factor I.

For instance, in the building energy case, a PID controller can be used to command a heating system while observing the room temperature as an output. In that way, the command will be calculated such that the room temperature is maintained at the user given set point even if a perturbation occurs.

1) Limits: PID controller is limited to a unique couple of control point and input point. Although methods have been developed in order to extend the number on control points, the counter part is a higher number of parameters to adjust in order to get a satisfying control.

Adjusting PID controller can be made using two main methods. The first one is analytic as it requires a model or a transfer function of the process we aim to control. From the equation of the model the three parameters of the controller can be calculated. Whether the model is given by analytic study, or identified, it is still an approximation of the real system. If the system changes, the model has to be rebuilt again as the PID parameters.

The second method is empirical as it is based on several manual adjustments of the P parameters until the system leads to the limit of instability. Then, the I and D parameters are calculated by a standard formula giving a good balance between stability and robustness of the controller.

PID controller does not fit our need as it actually does not perform an optimization task. The appropriate tuning of the PID parameters will eventually leads to satisfy constraints on the output of the system, however, all the works reside in the knowledge of the designer. Both parameters tuning methods require a considerable amount of time and are inherently linked with the dynamic of the building. Once again, a building does not have a fixed dynamic and can evolve over the time,by consequences, PID controller are not the appropriate method to control the building.

B. Model Predictive Command

An efficient control system requires information regarding the dynamics of the controlled system. One way to bring this information is to provide it a model of the system on which it can evaluate different solutions regarding constraints before applying the best one found to the real process. This approach is known as predictive controller system.

Such systems are composed by two main parts, a reference model of the system, and an adjustment mechanism. The model

simulates the future state of the system in a predefined time horizon from the actual state and a set of inputs. The results of the simulation are transmitted to the adjustment mechanism which have the choice between making more experiments or applying the best solution found to the real system. [8]

In the building energy management domain, this method allows to regulate the room temperature and to take into account various information such as windows opening, presence or weather forecasts.[9]

Limits First, getting a model of the system we aim to control may require a large amount of time. Creating a simulation of the energy dynamic within a building requires a large amount of information from the real case in order to match the simulation with the simulated results. Wall width, isolation capacities, heating and cooling devices specifications and time table of the usage of the building are essential information required. The building model must be first established then validated relatively to the real building behavior. As the adjustment mechanism essentially depends on the result of the simulation, any deviation of the model from the reality isn't taken into account. Thus, regulation solution found by the system may be optimal on the model, but sub-optimal in the real case.

Secondly, the adaptation mechanism heavily uses the simulation module. This implies that the computation time required in order to obtain the appropriate solution can be long depending on the number of tries made on the simulation and the duration of the simulation. Remind that we are in the general case of office building, which may mean dozen of independent input points and lead to a very large search space.

In the SAVER system, the learning of the building behavior is, by design, spreads in the independent learning of each Context agents. Scaling the system is rather simpler as it only requires to instantiate new Action agents that will, by themselves instantiate the needed Context agents.

VI. Conclusion

This paper shows how a group of agents with local interactions let to the emergence of an optimal regulation function.

The originality of this approach is that the SAVER regulation system is able to learn and self-adapt to the building without the help of any external resources such as an analytic model of the building nor a specific learning tool.

Two different experiments made on top of a professional building simulator show how the SAVER system converges to an optimal regulation function. We showed that for a particular external temperature, only one Context agent is enough for learning the appropriate set point in about ten steps. In order to obtain a global optimization on the full scale of temperature, only few dozen of agents are required. There is then no doubt about the ability of the system to scale to a large building with many controllable devices.

We will extend the functionality of SAVER following two ways:

- We refine the the night time set point regulation with an additional constraint on the morning energy consumption peak.[10] [11] This will be done by adding an additional Constraint agent with a minimization criticality function that will send its state to the control.
- We multiply the number of Action agents in order to show how their local cooperative behavior lead to the satisfaction of the Constraint agents. This is also a way to evaluate the ability of the system to scale to larger building with dozen of controllable equipments.

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