A mixed (centralized/distributed) solving approach for energy management problem in dwelling

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Abstract— *The global dwelling energy management problem can be formalized as an optimization problem of energy consumption/production. An optimal solution for the home energy management problem is usually solved by centralized solvers. The solver gets the totality of the thermal model of the dwelling but also each appliance composing the system. Nevertheless, this centralized resolution has some limits due to some particular appliances. For example: the appliances with a non-sharable model because of the manufacturer, the appliances that need some precisions that cannot be included in their standard representation used by the solver, the appliances which require specific solvers and the appliances which possess a heuristics solving rules. This work proposes to combine the centralized solving approach for energy management problem in dwellings with a multi-agent solving system. The multi agent system provides the possibility of integrating specific models in the global solving of the problem. The proposed system is a mixed centralized/decentralized approach for the solving of global energy management problem.*

Keywords: Multi-agent systems, Energy Management in dwellings, Optimization, Home automation system, Mixed integer linear programming.

1. Introduction

Reducing housing energy costs is a major challenge of the 21^{st} century. In the near future, the main issue for building construction is the thermal insulation, but in the longer term, the issues are those of "renewable energy" (solar, wind, etc) and "smart buildings". Home automation system basically consists of household appliances linked via a communication network allowing interactions for control purposes [1]. Thanks to this network, a load management mechanism can be carried out: it is called distributed control in [2]. Load management makes it possible for inhabitants to adjust power consumption according to expected comfort, energy price variation and CO_2 equivalent emissions. A home energy management system is able to determine the best energy assignment plan and a good compromise between energy production and energy consumption [3]. In this study, energy is restricted to the electricity consumption and production. [4], [3] present a three-layer (anticipative layer, reactive layer and device layer) household energy control system. This system is both able to satisfy the maximum available electrical power constraint and to maximize a ratio between user satisfaction and cost. The objective of the anticipative layer explained in [5] is to compute plans for production and consumption of services.

Uniqueness of housing systems involves a set of new issues in control system science: it is necessary to develop new tools [6], [7], [8] and algorithms [9], [10] for globally optimized power management of the home appliances, able to anticipate difficult situations and to take into account the actual housing system state and the occupant expectations.

The approaches solving the energy management problem in living places can be split into two groups:

- The approaches solving large dimension optimization problems. It has been tackled using a mixed integer linear programming approach that can manage thousands of binary and continuous variables in [9], [10], [11]. Ways of transforming an energy management problem into a MILP, which is a regular problem, have been shown. These approaches are noted "centralized solving approach of the energy management problem" due to the use of a central MILP solver that contains the general mathematical formulation of the problem. The global solution of the problem is then computed locally in this solver.
- The approaches solving singular problems and proposing "distributed solving of energy management problem". Multi-agent approaches have been used to manage services that can only be modeled by nonlinear equations [12], [6], [7], [13], [8].

The multi-agent approaches have some advantages but cannot ensure an optimal solution of the energy management problem contrary to the centralized approaches. The centralized ones have also some limits due to requirements on models. For example, the appliances with a non-sharable model, the appliances that need some precisions that cannot be included in a linear model (as a washing machine with a lot of perturbations and/or particular actions), the appliances which need non-linear optimization, and the appliances which possess heuristics solving rules.

This work proposes to solve the energy management problem by combining centralized and distributed solving approaches. This approach is noted mixed solving of the energy management problem.

The organization of the paper is as follows, firstly, the problem is presented and the need of a mixed solving approach is discussed in details (section 2) followed by the principle of mixed solving approach (section 3). The implementation of the approach is presented in (section 4). Finally the conclusion is drawn in (section 5).

2. Problem description

In this paper, energy is restricted to electricity consumption and production. Each electrical activity is represented by an amount of consumed/produced electrical power; it is called service and can be supported by one or several appliances.

Housing with appliances aims at providing comfort to inhabitants thanks to services which can be decomposed into three kinds: the end-user services that produce directly comfort to inhabitants, the intermediate services that manage energy storage and the support services that produce electrical power to intermediate and end-user services. Support services deal with electric power supplying thanks to conversion from primary energy to electricity. Fuel cells based generators, photovoltaic power suppliers, grid power suppliers such as EDF in France, belong to this class. Intermediate services are generally achieved by electrochemical batteries. Among the end-user services, well-known services such as clothe washing, water heating, specific room heating, cooking in ovens and lighting can be found.

A service with index i, denoted as SRV_i, transforms energy in order to meet a user's need via one or several appliances. A service is qualified as *permanent* if its energy consumption/production covers the whole time range of the energy assignment plan such as heating service, otherwise, the service is referred to as a *temporary service* such as cooking or washing service.

A temporary service is characterized by the duration and desired end time of the operation. The flexibility of this service comes from the possibility of shifting its operating time, i.e. bringing it forward or delaying the service.

A permanent service is characterized by a quantity of energy consumed or produced. The flexibility of this service comes from the possibility of modifying the energy quantities consumed/produced throughout all the periods (decrease or increase in energy consumption or production at a given time).

An important issue in Home Automation problems is the uncertainties that have to be taken into account. For instance, solar radiation, outdoor temperature or services requested by inhabitants are not exactly known. In order to solve this issue, a three-layer architecture is proposed in this paper: a local layer, a reactive layer and an anticipative layer.

The *anticipative layer* is responsible for scheduling end-user and support services taking into account predicted events and costs in order to avoid, as much as possible, the use of the reactive layer. Various forecasted information about future user requests and available power resources and costs are needed to compute anticipative plans. This layer has slow dynamics and includes predictive models. Let us assume a given time range for anticipating the energy needs (typically 24 hours). The sampling period of the anticipative layer is denoted $\triangle$. The *reactive layer* aims at adapting the anticipative plans to the actual requests and environmental conditions.

The formulation of the energy management problem contains both behavioral models with discrete and continuous variables, differential equation and quality models with non-linearities such as in the PMV model. In order to get mixed linear programs which can be solved by well known efficient solvers, transformations of the previous equations have to be done. The problem is then solved by a centralized solver. The solver takes the models of different services, constructs the problem, and provides the solution.

This centralized solving problem has some limits:

- the appliances having a model non-shared by manufacturers: usually, manufacturers keep their appliances models. From the centralized solver point of view, the model of these appliances cannot be included in the problem solving. The solver can only take into account an unsupervised service reducing accuracy.
- the appliances that need some precision and cannot be included as linear model. For example, a washing machine, more precision is expected in the control like water temperature set-points, length of some phases,... These fine controls cannot be included in a general linear model.
- the appliances having a non-linear model: for example, a heat pump is modeled by a non-linear model dependant of the outdoor temperature. The local problem solving can be done by using a non-linear optimization method such as Nelder Mead or SQP. These categories gather appliances with non-linear model and appliances that can be managed by specific solvers.
- the appliances that are managed by user-defined specific heuristic rules: These appliances have some "behavioral rules". For example, positions of shutters can be programmed with rules defined by inhabitants. This is the case of "end user programming". In this case, the behavioral rules provide the solution without the need of any optimization. The solver must take into account the chosen solution in the global problem solving.

The following section presents the solution proposed to integrate these types of appliances in the global solving of the problem.

3. Principle of mixed solving approach

The system consists of three main parts (Figure 1):

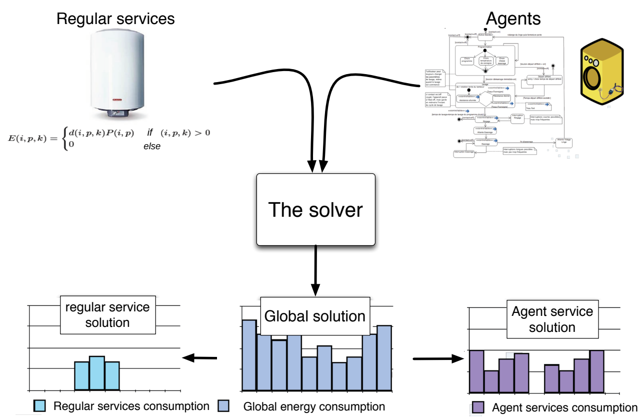

Fig. 1: Global architecture of the mixed solving system

Fig. 2: Solving process during one step

- The regular services:consist of the appliances having a linear model and can be integrated directly into the energy management problem.
- The agents:consist of the services that do not have a linear model and should communicate with the solver to give their *energetic profiles*. The steps of the solving process and the protocol of communication are presented in the following parts.
- The solver consists of a regular solver with the ability to communicate with agents. The solver integrates the information sent by the agent's local solvers with regular service models in order to generate a global problem to solve.

There is only one communication needed between this regular services and the solver. At the beginning of the solving process, the solver receive the linear model from the regular services. The models are used all along the solving process.

In the case of agents, some communications are needed. Each exchange between the agents and the solver is considered as a step in the solving process. In each step, an intermediate problem is created by the solver then computed. The solver decides which information is needed to be sent to the agents in the next step. The agent takes into account the information sent by the solver and sends energetic profiles. The solving process is presented in the following in three parts:

- The progress of the problem solving during one solving step.
- The solver's behavior during the solving process.
- The agent's behavior during the solving process.

3.1 One step solving

Figure 2 presents the information exchanged between the solver and the regular services and the agent services during the first step in the solving process.

First, the solver receives the linear models of the regular service. This operation is the initialization of the problem. Once initialization is done, the solver computes the *relevance indicator*. It is an indicator with the purpose to direct the local solving problem in the agent. When this indicator is computed, it will be sent to all agents.

The agents don't have any information about the environment but they have the ability to solve their own local problem. When agents receive the relevance indicator, they compute their solutions taking into account this indicator serving as information about their environment. They obtain several solutions, which are called *energetic profiles*. It is the consumption for the concerned agent for each period of the optimization horizon. All theses profiles are sent back to the solver. The solver includes them in the problem To be solved at this step. Then the global problem with all the services is solved at this step.

After the first step, the solver begins a new step by computing the relevance indicator. The relevance indicator is computed taking into account the received *energetic profiles* sent by the agents in order to improve the global solution each step in the solving process.

3.2 Solver's role

The solver has two tasks to do in each step. In order to formulate these tasks, we introduce some notations:

- k is the index of anticipative period
- $\mathcal{S}$ is the set of services
- $\mathcal{S}^L$ is the set of *regular services*
- $\mathcal{S}^D$ is the set of *agent services*
- S is a service included in $\mathcal{S}$
- E_k^{max} is the available energy during the period k before any optimisation
- $E_k(S)$ is the consumed energy by the *regular service* $S \in \mathcal{S}^L$ during the period k
- $E_k(S, i, \mathbb{P}_k)$ is the consumed energy by the *agent service* $S \in \mathcal{D}^L$ during the period k for the i^e profile

- C_k is the cost of energy during the period k
- $\upsilon(S)$ is the characteristic of inhabitant request for the service S
- $D(\upsilon(S))$ is the dissatisfaction of the *regular service* $S \in \mathcal{S}^L$
- $D(\upsilon(S), i, \mathbb{P}_k)$ is the dissatisfaction of the *agent service* $S \in \mathcal{S}^D$ for the i^e profile
- $\mathbb{P}_{k,\forall k}$ is the relevance indicator for the current step of resolution

a) Optimisation problem: Each step, the solver computes a linear problem to find a solution. The *regular services* models are represented in [14]. This problem is extended by including *agent services*. Some equations are added to take into account the *agent services*. A new set of variable for each *agent service* is introduced (see equation 1). $\zeta_i(S)$ is a binary variable whose value is 1 if the profile i of the *agent service* S is chosen by the solver, 0 otherwise.Combined with equation 2, ensure the solver to keep only one profile for each *agent service* in the solution.

$$\zeta_i(S) \in \{0, 1\}, \forall i \tag{1}$$

$$\sum_i \zeta_i(S) = 1 \tag{2}$$

The criterion to minimise is modified and becomes a two parts criterion (3).

$$J_{iter} = \sum_{S \in \mathcal{S}^L} \left(\sum_k C_k E_k(S, \theta(S)) + \lambda \times D(\upsilon(S, \theta(S))) \right) + \sum_{S \in \mathcal{S}^D} \sum_i \zeta_i \left(\sum_k C_k E_k(S, i, \mathbb{P}_k) + \lambda \times D(\upsilon(S), i, \mathbb{P}_k) \right) \tag{3}$$

There are two different parts in this criterion, one part concerning *regular services* and one part for *agent services*. They are designed on the same scheme to have an a standardized criterion. This scheme split into two influences:

- The influence on the cost: the global energy cost must be minimized.
- The influence on the inhabitants: the dissatisfaction of the inhabitants must be minimized.

Those influences can be found in both *regular services* part and *agent services* part. But there is a fundamental difference between these two parts, and it is symbolized by the sum on the index i in the *agent services* part. The solver keep only one profile for each *service agents*. For each profile, the solver receives one consumption plan and an associated dissatisfaction. The sum in the criterion with binary variables forces to keep only one profile per agent for the minimisation.

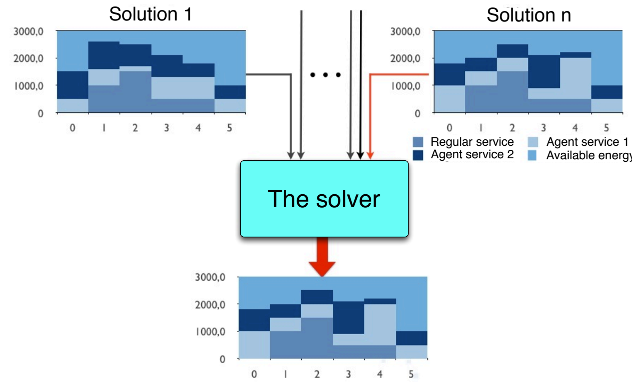

Fig. 3: Solution found by the solver

Figure 3 shows the complexity of the problem to be solved at each step. Each *service agent* provides n profiles, if there are m *singular services*, then there are n^m different solutions. But the solver has to minimise the criterion to keep one.

b) Relevance indicator: The relevance indicator is computed during each solving step to direct the local solving process of service agents for the next step. After the solving step j, the relevance indicator is computed with the equation 4. The purpose of this approach is to share the information about the energy consumption and price between solver and service agents. The service agents integrate the received information in their local solving process of the step j+1. This indicator is high when the consumed energy is important or/and when the energy is expensive. This rules aim to obtain a better solution that minimize J_{iter} in the step $j+1$. During the first step, the consumption of the *agent services* is null.

$$\mathbb{P}_k^j = \frac{1 + E_k^{max}}{1 + E_k^{max} - \sum_{S \in \mathcal{S}^L} E_i^{j*}(S)} C_k \tag{4}$$

3.3 Role of the agents

An agent is dedicated to a specific entity whose behavioral model cannot be linearized and then taken into account directly by the solver. In this part, the algorithm used by agents are explained using an example of washing machine service agent.

The washing machine service agent has its internal state model. The states are shown by figure 4. They consist in:

- some behavioral states like heating, prewash, washing and spin-drying.
- two states representing the begining and the end of the service
- some states denoted *wait i* represent the waiting time between behavioral states
- some states modeling the interuption whithin each state, denoted *interupted state*

The normal behavior of the washing machine service is given by the state sequence scenario [start, heating, prewash, washing, spy-drying, end]. The other states are only visited when the service agent tries to find some neighbouring profiles in order to respond to some criteria sent by the solver.

Each visit to an *interrupted state* has a fixed time period $\tau_{interrupted}$. It is possible to visit the *interrupted state* more than once in order to increase the interruption time in a state. For example, in the state sequence scenario [start, heating, interupted heating, heating, interrupted heating, prewash, washing, spy-drying, end], the time spent in the interupted heating state is $2 * \tau_{interruption}$.

A behavioral profile is the state sequence scenario with the date of each state visit. The behavioral profile is caracterized by:

- the starting time of the service
- the number of visits to each *interrupted state* and the number of visits for each *wait i* state
- the date of each visit to *interrupted states* and *wait i* states.

These characteristics are denoted in the following *parameters of behavioral profile*. It is interesting to note that a behavioral profile is computed in order to be converted into an energetic profile. The energetic profile consists on the energy consumed by the service in each period of the anticipative horizon. The energetic profile is then sent to the solver.

The Agent satisfaction is computed according to the energetic profile. The satisfaction depends on the number of visited interupted states and also on the effective ending time regarding its expected value for the occupants. The increase in the number of interruptions affects the agent satisfaction.

3.3.1 Agent solving algorithm

The agent solving algorithm is presented in figure 5.

Firstly, the agent receives the relevance indicator. The relevance indicator consists of information about the penalisation and the energy price during the anticipative horizon. The agent receives also the choosen energetical profile at step j.

The first step in the algorithm is to normalize the values of relevance indicators (5). The goal of this step is to obtain $RI_{k(normalized)}$ that can be used in the computation of CA_k, the agent coefficient. It is composed both on the information received from the solver and on the local satisfaction computed by the agent.

$$RI_{k(normalized)} = RI_k / Max(RI_k) \tag{5}$$

The second step consists on the computation of the agent coefficient CA_k. The CA_k merges the information about the prenalization, the energy price and the agent disatisfaction denoted I_k (6).

$$CA_k = RI_k + \lambda * I_k \tag{6}$$

In order to generate an enegertic profile, the first step is to compute the behavioral profil. The parameters of the behavioral profile are listed above. The first one in the starting time of the service. We begin by finding the best intervals over 6 periods in the 24 hour horizon according to the values CA_k. For each interval j we compute X_j (7).

$$X_j = (\sum_{k \in [j, j+6]} CA_k)/6 \tag{7}$$

We denote $X_{j_{min}}$ the minimum of the list X_j.

Then we try to find the intervals having no significant difference with $X_{j_{min}}$. We denote L_{min}, the list:

$$L_{min} = \{k/1 - (X_{j_{min}}/X_k) < 0.1\} \tag{8}$$

The interval χ with the maximum variance in L_{min} is chosen for the optimization. The starting time of the service corresponds to the starting time of the chosen interval χ.

The parameters of the optimization are presented in figure 6 where N_{Si} is the number of interuptions in the state Si. W_{Si} is a value to select the time for interruption within the state.

A branch and bound optimization is achieved on this parameter (Figure 7) within the chosen interval χ. Each agent solves the optimization problem with this function. It represents the minization of the energetic cost and dissatisfaction from a local point of view. The function to be minimized 9 is similar to the one presented for the solver.

$$min_{\theta^{j+1}} J^{k+1} = \sum E_k(\theta^{j+1}) \mathbb{P}_k^j \mathbb{T}_k^j + \lambda D_i(\theta^{j+1})) \tag{9}$$

θ^{j+1} represents the parameters of the user that define the usage conditions. The function is composed of two parts: the first one is the influence of the energetic cost and the second one is the influence of the satisfaction of the agent.

The results of this optimisation is a list of parameters required to generate the behavioral profile (parameters of behavioral profile). Then, the energetic profile can be computed and sent to the solver to be integrated in the global problem solving.

4. Implementation

The implemented system consists of five components (figure 8):

- the classical regular solver used in [14]
- the solver that solves global problem composed from regular problem and agent problems
- the broker agent is a communication component that receives all the local problems from service agents

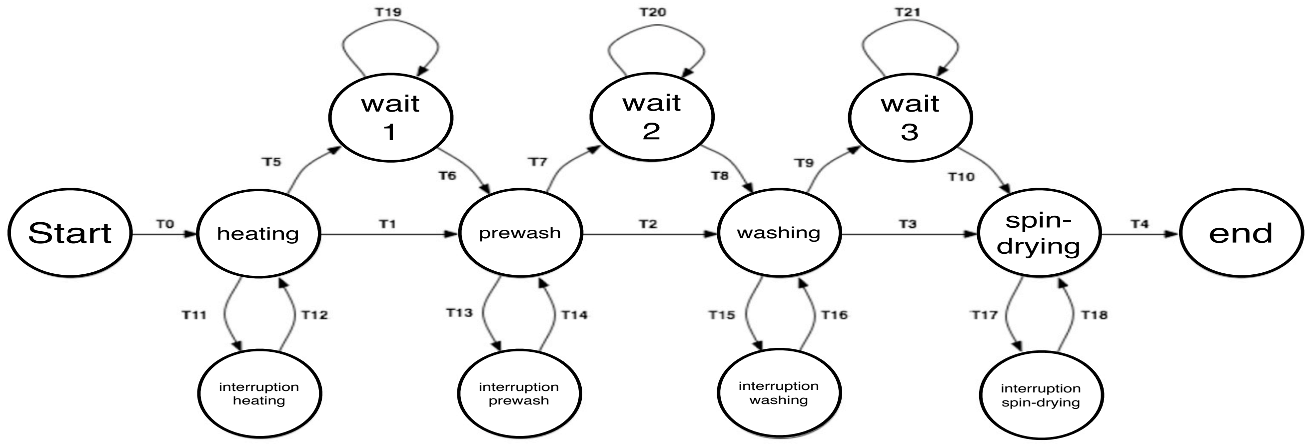

Fig. 4: State model of the washing machineservice agent

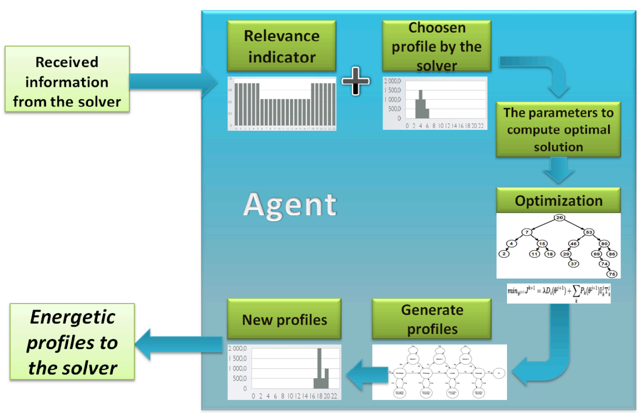

Fig. 5: Solving algorithm in the agent

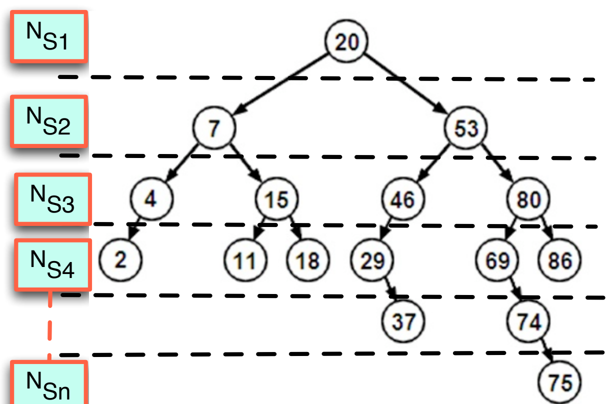

Fig. 7: Optimization using branch and bound

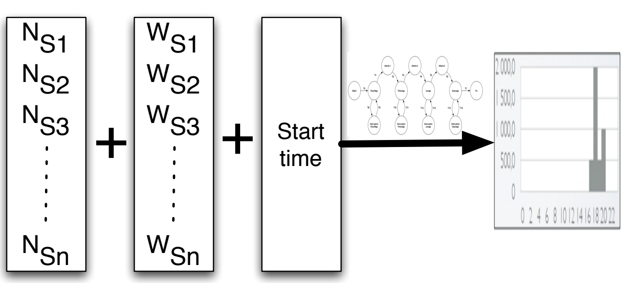

Fig. 6: Parameters of a profile

and construct one global service agent problem. This problem is sent then to the global solver. The broker receives also the relevance indicator from the solver and dispatches the information to service agents

- the service agent with the capabilities to solve a local problem.

The system is tested by using two service agents and some regular services. Figure 9 presents simulation results.

5. Conclusion

In this paper, the energy management problem is solved by combining centralized and multi-agent solving approaches. The multi agent system added to the MILP solver provides the possibility of integrating singular, i.e. not MILP, appliance models in the global energy management problem to

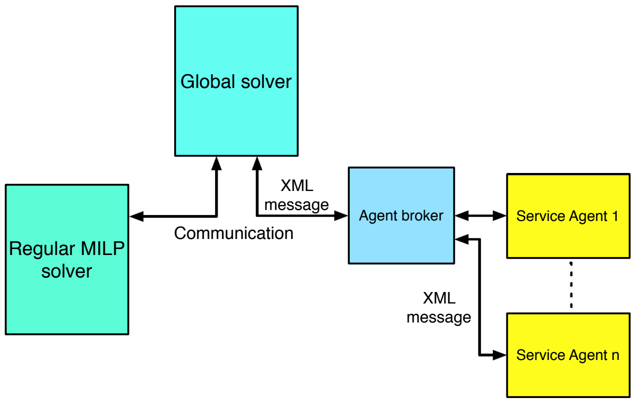

Fig. 8: The composant of the mixet solving system

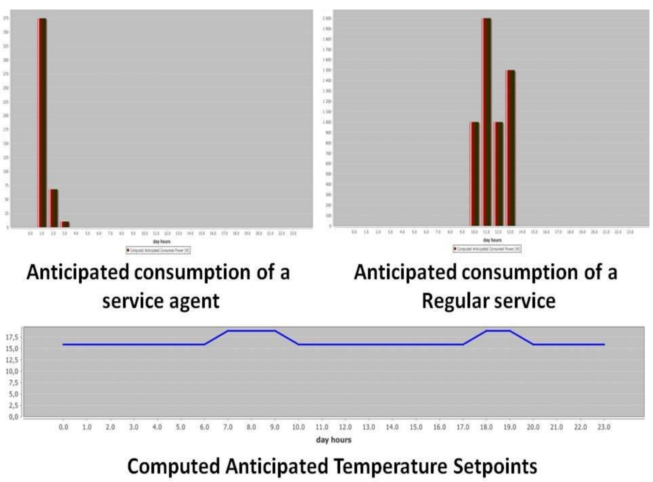

Fig. 9: Anticipating regular and service agents

be solved. The proposed approach has been implemented and tested. Conversely to centralized solution, the solution resulting from a mixed approach is not garanteed optimal solution. The number of steps used in the solving process affects the resulting solution. The algorithm used in the solver to generate the relevance indicator affects also the global solution. Genetic algorithms can be studied and introduced at this stage in order to improve the global solution.

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