Multi-Agent-Based CBR Recommender System for Intelligent Energy Management in Buildings

Tiago Pinto, *Member, IEEE*, Ricardo Faia, Maria Navarro-Caceres, Gabriel Santos, Juan Manuel Corchado, and Zita Vale, *Senior Member, IEEE*

***Abstract*—This paper proposes a novel case-based reasoning (CBR) recommender system for intelligent energy management in buildings. The proposed approach recommends the amount of energy reduction that should be applied in a building in each moment, by learning from previous similar cases. The *k*-nearest neighbor clustering algorithm is applied to identify the most similar past cases, and an approach based on support vector machines is used to optimize the weight of different parameters that characterize each case. An expert system composed by a set of *ad hoc* rules guarantees that the solution is adequate and applicable to the new case scenario. The proposed CBR methodology is modeled through a dedicated software agent, thus enabling its integration in a multi-agent systems society for the study of energy systems. Results show that the proposed approach is able to provide suitable recommendations on energy reduction, by comparing its results with a previous approach based on particle swarm optimization and with the real reduction in past cases. The applicability of the proposed approach in real scenarios is also assessed through the application of the results provided by the proposed approach on a house energy resources management system.**

***Index Terms*—Building energy management, case-based reasoning (CBR), energy efficiency, multi-agent systems (MAS).**

I. Introduction

THE world has increased the consumption of energy and in particular, the consumption of electricity. The EU guidelines toward a low-carbon society and the recent EU Winter Package [1] frame consumers as a central piece in future power systems, being the consumption flexibility the most promising solution for the new challenges [2]. The consumer thus becomes an active resource in context of the new paradigm of smart grids (SG) [3]. Thereby, management systems should include new characteristics and advanced functions, namely the management of electric vehicles [4], the interface with external operators, and others. These management systems are defined as smart home systems [3]. The smart home represents a house with network communication between all devices allowing the control, monitoring, and remote access of the management system [5]. Several works deal with the smart home as a house management system to effectively manage consumption, storage, distributed generation and the participation in demand response (DR) events [6].

With automatic participation in DR events, the house management system can reduce the electricity consumption based on the interaction with an external entity. This interaction is performed by smart meters, which enable bidirectional communications between the house and the grid [7], with measurements in small time intervals, the energy costs information in real time and the remote control of the electricity demand management [8], [9].

Building energy management systems (BEMs) play a crucial role in this scope, as they are able to support consumers' decisions in adapting their consumption without compromising their comfort [10], [11]. However, deciding how much flexibility should be asked from each consumer when required is not an easy task as it depends on each individual consumer's habits and comfort. This paper addresses the problem of deciding the amount of reduction that should be asked from consumers in moments when such is needed from the system. This is done by proposing a novel case-based reasoning (CBR) [12] system that uses previous cases of energy reduction in a building to decide which amount should be applied to a new case.

CBR systems have been applied to energy system problems, e.g., in [12] and [13], and have shown great capabilities to deal with the dynamic characteristics in this domain. In fact, artificial intelligence approaches, such as multi-agent systems (MAS) [14] and machine learning [15] are common solutions in power and energy systems. These approaches have also shown to be advantageous when associated to recommender systems, e.g., [16], as discussed in detail in Section II.

The successful application of CBR and MAS as recommender systems in the power and energy domain turn these approaches into promising solutions to solve other problems in the field that still lack adequate solutions, such as the recommendation of the energy amount to be reduced in the intelligent energy management in buildings.

This paper proposes a MAS society that is composed by several independent MAS, directed to the modeling and simulation of specific parts of the energy system. In this way, the study of the impact of the energy system in the small consumer is facilitated, as well as the interaction between the small players and the external system. A novel CBR [12] recommender agent is incorporated in this MAS society to enable the connection between the building and the external system. The CBR model determines and recommends to the user the level of instantaneous reduction in a building that could be applied without

Manuscript received August 12, 2017; revised March 20, 2018 and June 5, 2018; accepted October 6, 2018. Date of publication November 13, 2018; date of current version February 22, 2019. This work was supported in part by the EU's H 2020 research and innovation programme under the Marie Sklodowska-Curie Grant Agreement 641794 (project DREAM-GO) and Grant Agreement 703689 (project ADAPT), in part by the FEDER Funds through COMPETE program, and in part by the National Funds through FCT under the Project UID/EEA/00760/2013. *(Corresponding author: Tiago Pinto.)*

T. Pinto, M. Navarro-Caceres, and J. M. Corchado are with the BISITE Research Centre, Universidad de Salamanca, Salamanca 37008, Spain (e-mail: tpinto@usal.es; maria90@usal.es; corchado@usal.es).

R. Faia, G. Santos, and Z. Vale are with the GECAD, Instituto Politecnico do Porto-Instituto Superior de Engenharia do Porto, Porto 4200-072, Portugal (e-mail: rfmfa@isep.ipp.pt; gajls@isep.ipp.pt; zav@isep.ipp.pt).

Digital Object Identifier 10.1109/JSYST.2018.2876933

compromising the comfort of the users, considering the needs from the system. The proposed CBR model considers a database (DB) of registered past scenarios referring to the same building, and generates a reduction value based on the existing cases. First, the *k*-nearest neighbors (*k*-NN) clustering algorithm [17] is applied to identify the most similar cases to the current one. After the similar cases are identified, a support vector machine (SVM) [18] is applied to optimize the weights attributed to each variable that characterizes each case, in order to reach the optimal combination of the similar cases with the aim of achieving a solution for the new case. Finally, the achieved solution is refined by means of an expert system [19]. After the final solution is achieved, the solution is sent to the SCADA house intelligent management (SHIM) [20], which is a BEMS that decides which loads should be reduced based on the output results proposed by the CBR agent and taking into account the current context and the users' comfort. In summary, the main original contributions of this paper are as follows:

1) Novel CBR model to determine energy consumption reduction in buildings.
2) Proposal of SVM approach to optimize the influence of the different parameters that characterize a case.
3) Innovative agent-based recommender system integrating the proposed CBR approach.
4) MAS society that is composed by several independent MAS, directed to the modeling and simulation of specific parts of the energy system.

After this introductory section, Section II provides an overview on the related work in the field. Section III provides a description of the MAS society, and Section IV presents the proposed model, including a description of the applied techniques. Section V presents the case study and discusses the achieved results. Section VI discusses the practical implications of this paper, and the main conclusions of this paper are provided in Section VI.

II. Related Work

A. Modeling Agents With a CBR Architecture

The CBR can be implemented by different kind of agents. One of them is the case-based planning (CBP) agent. A CBP agent is a particular type of CBR agent, which uses a CBR system to generate plans from cases. A good example is presented in [21], proposing a CBP to control electric power networks. Other proposal is to wrap the CBR architecture in a belief-desire-intentions (BDI) agent. A BDI agent incorporates a "formalism" in which the reasoning process is based on the concept of intention [22]. A straight relationship between CBR systems and BDI agents can also be established if the problems are defined in the form of states and actions [22]. In particular, the states and the objectives of the CBR can be considered as beliefs in a BDI implementation. The intentions, represented as a set of actions to achieve the agent goals, provoke a change between states. As the agent remembers the actions applied in the past, it also knows the results when an action is carried out in a concrete moment. Finally, the desires are the final states the agent wants to achieve based on previous experience. CBR-BDI agents are widely used to solve problems in very different domains. For example, Luong *et al.* [23] apply a CBR-BDI agent as a master agent to create a role video-game. Navarro-Cáceres *et al.* [24] develop a CBR-BDI agent capable of generating music based on the user's opinion. Yang [25] models a BDI agent to save energy applying a CBR behavior.

Recently, some works have been proposed where a CBR architecture is distributed in MAS. For example, the platform proposed in [26] aids clinical decision based on MAS and CBR along with medical knowledge and Jaiswal *et al.* [14] proposes an agent organization in which a CBR architecture is implemented to optimize energy consumption. Although experimenting the implementation of such an approach could be interesting in the current work, e.g., by having independent agents to execute the *k*-NN, SVM, and expert system phases, it does not bring direct benefits for the proposed model. The different phases are directly connected and the information flow is sequential between the different phases, as described in Section IV; therefore, this approach is not the focus of this paper, rather the incorporation of the proposed CBR model in a MAS approach through a single software agent.

B. CBR as Recommender Systems

A recommender system consists of a filtering system that can predict the preference that a particular user gives to an item. Recommender systems can be applied following two different approaches: content based or personality based. Collaborative filtering uses information about past decisions to recommend a new item. This model is able to recommend a new item based on the properties that it shares with other items and the interest the user has in, expressed by a query [26].

There is a parallelism between CBR architecture and the recommender system behavior. From a CBR viewpoint, the query serves as a problem specification, the item descriptions are cases, and similarity-based retrieval techniques select the best-matching items [26]. Therefore, the CBR has been widely used to make recommendations about different items. For example, Tkalčič *et al.* [27] makes use of CBR and affective labelling to recommend image.

Recommender systems have been also applied to energy issues. Ge *et al.* [28] propose a mobile recommender for energy management. Ballenger *et al.* [29] develop an interface that makes recommendation about the human behavior in order to save money and energy in a domestic environment. Luo *et al.* [30] make a recommender system for energy saving appliances oriented to SG residential users. The work presented in [13] proposes a CBR system to support users' decisions in the choice of the most appropriate energy resource management (ERM) algorithm, depending on the context of use and execution time versus quality of results requirements. However, the proposal of CBR-based recommender systems for energy reduction in buildings consumption, such as the model proposed in this paper, is not found in the literature.

C. Energy Management Using CBR Systems

In accordance with the requirements imposed by the EU for reducing CO_2 emissions, where buildings are considered to be the casters of most of these emissions, energy efficiency should be increased, by decreasing the consumption of unnecessary power; and buildings should be able to respond to DR events, where some need for reduction can be asked in specific times (e.g., during times when renewable-based generation is lower). Although the existing BEMS are able to provide some contribution in this direction, there is a significant difficulty in identifying the exact values of consumption reduction that could be asked or applied to each consumer.

Sharma *et al.* [31] present a mathematical model for the optimal energy management of residential buildings and propose a centralized energy management system. The mathematical model was constructed including the model of each component and their physical constraints, parameter settings, external information, and user preferences to generate optimal decisions. By requiring the exact information of all parameters, this model becomes limited in terms of application, as it can only be applied in contexts in which all the information are available. The CBR approach proposed in this paper uses historical data from past knowledge to learn from past experiences, thereby, becoming much more open to a wide set of new application scenarios. The execution time and simplicity of implementation (as the proposed model does not require the mathematical formulation of all components and settings) are other relevant advantages of the proposed model.

An application of CBR in the context of buildings, more precisely in green buildings, can be seen in [12]. In this paper, authors developed a model using CBR and text mining, which tries to take advantage of the evaluations of green buildings and their conclusions and solution, to learn the lesson to be applied in new cases, with the objective of predicting if the new buildings will be successful in their evaluation. The use of CBR in buildings has been widely used for predicting consumption as can be observed in the following sources [32], [33]. In this paper, on the other hand, CBR is used to recommend decisions on how much electricity can be reduced in a house.

The combination of CBR and MAS in the energy field has some applications in recent literature, as compared by Table I. In this table, the "CBR and MAS connection" column describes if the model or system uses a MAS approach to model the different phases of the CBR cycle (MAS in CBR) or if the CBR is incorporated as an agent in a MAS (CBR in MAS).

Xu *et al.* [37] present a system that incorporates a CBR in a MAS to solve some existing problems in energy efficiency management systems. The proposal makes a deep study to identify problems in energy management systems in China and tries to address these challenges with an MAS. Chamoso *et al.* [21] study the human costs in the identification and revision of transmission towers (TT) to look for possible problems and solutions. To make this process more efficient, it develops a CBR-BDI agent that collaborates with a multi-agent system in conjunction with different algorithms to reduce the number of TT to be reviewed in an electrical network. Chamoso *et al.* [34] also present an agent-based tool with a CBR cycle incorporated to reduce the maintenance cost of energy distribution networks.

Jaiswal *et al.* [14] provide a study about how wireless sensor and actuator networks are used to remotely monitor and control the environment according to the decisions made by the centralized reasoner, in which a CBR agent is involved. Ayzenshtadt *et al.* [36] present a distributed retrieval system, MetisCBR, for the building (including electrical issues) design domain, where agents work in groups (containers) on resolving of user queries built with a semantic description model Semantic Fingerprint. The main aim of this approach is to carry out a basis for a considerable retrieval tool for architects, where the combination of CBR and MAS helps to achieve valuable and helpful search results in a comprehensive building design collection. Yang [25] develops an energy-saving system where a CBR information agent is designed to manage Web service and ontology techniques. The system can explore related technologies to establish a Web service platform, and study how to construct cloud interactive diagrams to employ Web service techniques for energy-saving through a CBR information agent. MEnSuS [44] is another relevant approach for energy management of cloud data centres.

In summary, the application of CBR approaches and even the combination between CBR and MAS to solve problems in the energy system domain is not new. Several relevant models can be found in the literature to address several distinct problems. This makes CBR approaches promising solutions to deal with further distinct problems. The application of CBR models for energy management in buildings, and, in particular, for the recommendation on the most suitable amounts of energy reduction that should be applied in each moment, has not been experimented before this paper. It is in this domain that this paper provides its contribution, by proposing a specific CBR model to address this particular problem.

III. MASs Society

Power and energy systems are complex and dynamic environments, characterized by constant changes. Studying such complex systems requires complex modeling and simulation tools, to enable capturing the complete reality. For this purpose, this paper proposes an agent architecture that is composed by multiple independent MAS, directed to the study of specific parts of the system, which, through the interaction of the involved agents, enable modeling the system as a whole.

The different MAS that compose the MAS society are developed in JAVA language and use the JADE platform to implement the agents, making the whole system FIPA (Foundation for Intelligent Physical Agents) compliant. In addition, to achieve interoperability between systems, different MAS use ontologies that allow the sharing of vocabulary and mapping of concepts between systems, so that they can communicate. The ontologies are formulated in OWL DL, with representation in RDF/XML and are presented in [45]. In order to allow the interoperability between the systems, ontologies enable them to speak the same language and to understand the same concepts and terms, preventing different interpretations of the same information. Two types of ontologies are used. The first type is conceptual ontologies, which are the basis for communication between systems. These ontologies allow the description of the vocabulary that is shared between the systems. The second type of ontology is related to the procedural part of the systems (application ontology), and it is used to describe the way the systems work through the description of its services and communications, detailing inputs and outputs. The MAS society is represented in Fig. 1.

As shown by Fig. 1, the MAS society includes several independent MAS, which cover the entire energy system, from the simulation of wholesale electricity markets until the consumers' energy management.

The electricity market simulation is performed by the multi-agent simulator of competitive electricity markets (MASCEM) [46]. MASCEM accommodates the simulation of a diversity of market models through a multi-agent model that includes agents to represent the market operator, the system operator, buyers, sellers, and aggregators. MASCEM also enables the participation of external agents in market simulations, such as small players that are part of other systems, e.g., SG operators or other aggregators.

TABLE I
REVIEW OF CBR AND MAS APPROACHES TO ADDRESS PROBLEMS IN ENERGY SYSTEMS

Name	Year	Area	Problem	CBR and MAS connection	Application type	Agent Architecture	Novelty	Ref.
P.Chamoso, et al.	2018	Energy	Reduction of maintenance costs	MAS in CBR	System	Other	Virtual organization-based	[34]
B. Luong, et al.	2017	Informatics	Intelligent game mastering	CBR in MAS	Model	BDI	Narrative directors	[23]
M. Navarro, et al.	2017	Music	Generation Melodies	CBR in MAS	Model	BDI	Markov model	[24]
H. Abutair, et al.	2017	Informatics	Phishing detection	MAS in CBR	System	Other	Phishing Threat	[35]
S. Jaiswal, et al.	2016	Energy	Energy efficiency decision	MAS in CBR	Model	Other	Energy efficiency management system	[14]
V. Ayzenshtadt,	2016	Civil construction	Architectural designs	CBR in MAS	System	Other	Distributed artificial knowledge	[36]
P. Chamoso, et al	2015	Energy	Reduction of transmission towers	MAS in CBR	Model	Other	Virtual organization-based system	[21]
K.Y Xu, et al.	2015	Energy	Energy efficiency management	MAS in CBR	Model	Other	Ad-hoc CBR model for energy efficiency management	[37]
A. Talib, et al.	2014	Informatics	Assisting cloud service provider	MAS in CBR	Model	Other	Cloud computing	[26]
M. El Ajjouri, et al.	2014	Informatics	Intrusion detection	CBR in MAS	Model	Other	Hierarchical and	[38]
S.Y. Yang	2013	Energy	Energy saving operation mode	MAS in CBR	System	Other	Web service and ontology techniques	[25]
J. Fu, et al.	2012	Supply chain	Cost collaborative management	MAS in CBR	System	Other	Adaptive negotiated strategies	[39]
D.-X. Gu, et al.	2012	Energy	Safety evaluation decision making	CBR in MAS	Model	Other	Delphi approach and grey system theory	[40]
M. Navarro, et al.	2011	Informatics	Postman service	CBR in MAS	Model	Other	Temporal-Bonded	[41]
C. Pinzón, et al.	2011	Informatics	Denial of services attacks detection	CBR in MAS	Model	Other	Services-oriented architectures	[42]
W. Mikos, et al.	2011	Automotive	Nonconformance in thermoplastic injection	MAS in CBR	System	Other	Distributed environment	[43]
J. Bajo, et all.	2005	Environment	Air-Sea interactions evaluation and monitoring	CBR in MAS	Model	BDI	Direct mapping	[22]

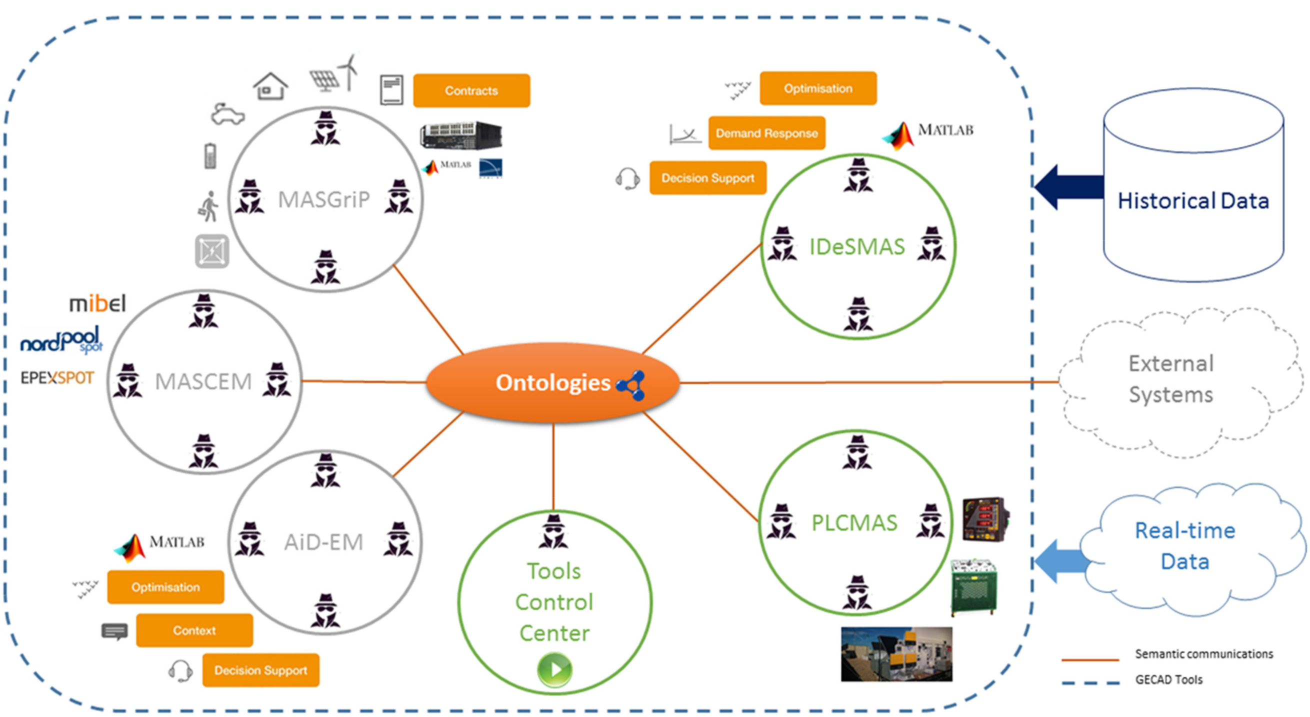

Fig. 1. Society of MAS.

The decision support to market negotiations is provided by another MAS, namely the adaptive decision support for electricity market negotiations (AiD-EM) [47]. AiD-EM includes agents to perform several tasks, such as the optimization of markets participation portfolio, and the decision support in auction-based markets and in bilateral contracts.

The modeling of smaller players at the microgrid and SG level is provided by multi-agent smart grid simulation platform (MASGriP), which simulates, manages, and controls the most relevant players acting in a SG environment [48]. This system includes fully simulated players, which interact with software agents that control real hardware. This enables the development of a complex system capable of performing simulations with an agent society that contains both real infrastructures and simulated players, providing the means to test alternative approaches (ERM algorithms, DR, negotiation procedures, among others) in a realistic simulation setting [49].

The intelligent decision support (IDeS)-MAS provides several services to external systems, namely forecast algorithms (i.e., artificial neural networks, SVM, and fuzzy inference systems) to be used to forecast consumption, generation, market prices, etc; DR programs; ERM systems for SG and MG levels, among others.

SHIM is a BEMS, whose main goal is testing, simulating, and validating new algorithms and methodologies to apply in house/buildings' management [19]. In order to obtain a realistic simulation, the platform comprises real equipment, such as several types of loads, mini and micro distributed generation (photovoltaic panels, wind generator), and storage systems that allow the simulation of the electric vehicles behavior.

To ensure the simulation of complex scenarios, SHIM is able to control real loads and virtual loads simulating the characteristics of the real ones. The system is composed of different modules that are grouped into three different parts: the data acquisition, the actuators, and the Intelligent Applications, where it included the learning algorithms. The detailed information of the structure can be found in [19]. The control of physical devices is accomplished by the connection to another MAS, the programmable logic controller (PLC) MAS. The PLCMAS allows us to test the scenarios in a real environment, being able to apply the results to physical devices, making them act accordingly. These devices are essentially lights, sockets, and HVAC, and need to be connected to a PLC.

Finally, an innovative tool is also used for the control and simulation of the MAS society. This Tools Control Centre (TOOCC) allows the simulation of various systems/algorithms independently, as well as the joint simulation of some or all systems present in the agent society. TOOCC also facilitates the automatic analysis of various simulations and knowledge sources, in an integrated manner.

The main advantage of the proposed MAS society is to enable the study and simulation of diverse and complex scenarios involving one or more systems devoted to distinct problems. Therefore, different complex dynamics between the agents of the different MAS can be accomplished and personalized, configured, and analysed using TOOCC.

The proposed MAS society enables modeling the power and energy system as a whole, by representing the most relevant players through software agents, in the respective specific MAS. However, it is still required to develop the adequate models to improve the interactions between consumers and the external system, by transmitting recommendations to consumers that reflect the needs from the system, in terms of consumption reduction or change in behavior habits. This is addressed by the proposed CBR agent, described in Section IV.

TABLE II
CHARACTERISTICS OF EACH CASE

Representation	Name of variables	Variable type	Measurement scale (converted scale)
x_1	Weekday	Numerical	Integer
x_2	Month	Numerical	Integer
x_3	Hour	Hourly	Real Number
x_4	Season	Numerical	Integer
x_5	External Temperature	Numerical	Real Number
x_6	External Humidity	Numerical	Real Number
x_7	Persons Number	Numerical	Integer
x_8	Electricity consumption	Numerical	Real Number
x_9	Electricity Generation	Numerical	Real Number
x_{10}	Electricity Tariff	Numerical	Real Number
R	Electricity Reduction	Numerical	Real Number

IV. CBR Recommender Agent

This section describes the proposed CBR approach, which is composed by four steps, as described in detail in the following sections. During the retrieve phase, the past cases that are similar to the new case are identified and retrieved from the DB. This is performed by applying the k-NN clustering algorithm [17]. By assessing the variables present in Table II, the k-NN choses the best k neighbors present in the DB (i.e., the most similar cases to the current one). The k-NN requires the specification of the number of k (neighbors). The algorithm will then select the k neighboring that minimizes the sum of the distance between the new case and the k most similar cases (3). A SVM-based method is then used to enable optimizing the importance of the different parameters that characterize each case for the calculation of the new result for the new case. Through the characteristics of the cases selected by k-NN, it is possible to arrive at a result for the new case using the SVM regression. The SVM optimizes the weight of each variable (7); thus, a smaller error, represented by (8), represents a better approximation. The originated solution is then refined through the application of another innovative aspect of this paper—an expert system that is composed by a set of *ad hoc* rules that guarantee that the solution is adequate and applicable to the new case scenario. Finally, the retain phase determines if the new case should be included in the DB, according to its similarity to the cases that are already part of the DB.

In order to apply the proposed model, it is necessary to have a DB that includes the historic previous cases. In this case, the available DB is constructed from the scenarios saved regarding the building for which the model will be applied. This DB has 11 different variables, which are collected and recorded from different sensors and other types of data collection systems. Table II represents all the variables and their types.

As visible from Table II, x_1 is a variable that represents the day of the week. This variable enables the system to know in which day of the week the case occurs. In this variable, Sunday is equivalent to 1, Monday to 2, etc., until Saturday, which is represented by 7. x_2 represents the month of the year, which is also represented by an integer value, where January corresponds to 1 continuing until December that is represented by 12. Variable x_3 represents the time (hour of the day) to which the case refers. A transformation is made from the time format to the numerical format (real number) so that the *k*-NN used in this paper can use the Euclidean distance to calculate the similarity. x_4 represents the corresponding season of the year, where summer is equivalent to 1, autumn to 2, winter to 3, and spring is equivalent to 4. The external temperature x_5, external humidity x_6, electric consumption x_8, electric generation x_9, and the electricity tariff x_{10}, are considered as real numbers. The number of persons x_7 should be represented by an integer number, which in some cases, it may be zero. The electric reduction R, is the result of the association between the variables and is considered as the resolution of each case. While the system uses the CBR before a new case, a reduction value will be generated.

For creating the DB, it is necessary to normalize the values of the variables. The normalization process converts raw values to standard scores, which requires selecting the values that span one range and representing them in another range. Normalization is often done by dividing each value by the highest value recorded in the DB. This type of process can cause problems when it is working with a DB where there are variables of different natures and different ranges of values. This type of normalization is limited by the possibility of distorting the values of the different variables, since the DB variables can have large discrepancy between each other and they are different in their types, (e.g., binary, integer, etc.). In this paper, 11 types of variables consider different data ranges (presented in Table II), which are converted to a scale from 0 to 1 through a statistical standardization process. By assuming that the data are approximated by the normal distribution, this is converted to a standard normal distribution, where the mean is 0 and the standard deviation (STD) is 1. Equation (1) presents the probability density function of the standard distribution

$$f\ (u) = \frac{1}{\sigma\sqrt{2\pi}}\ e^{-\frac{1}{2}\left(\frac{u-\mu}{\sigma}\right)^2} \tag{1}$$

where
- $f(u)$ probability density of normal distribution;
- μ mean and is equal to 0;
- σ standard division, and is equal to 1.

Equation (2) represents the cumulative probability function, and is the function of each real number u. This is called cumulative distribution function, since it accumulates the probabilities values, which are less than u

$$F\ (u) = \sum_{u_i \leq x} f\,(u_i) \tag{2}$$

where
- $F(u)$ cumulative probability distribution function;
- u_i discrete random variable.

Equation (2) calculates the cumulative probability for each DB value, thus, it enables obtaining a DB with all values between 0 and 1. In order to obtain the original values, it is simply necessary to apply the inverse function of the cumulative distribution.

A. Retrieve

The retrieve step is the most important task of the CBR cycle and it is the task in which the system will select the most similar cases. In the proposed methodology, this process employs the *k*-NN technique [17], clustering-based method [50], which is utilized to select the most similar cases. For this purpose, the *k*-NN algorithm uses a distance measure to analyze each case. This measure is the Euclidean distance and is expressed as

$$d\ (u_i, u_j) = \sqrt{\sum\nolimits_{r=1}^{n} \left((u_i) - (u_j)\right)^2} \tag{3}$$

where
- n dimensionality of the input vector, namely the number of attributes of the examples;
- r from 1 to *n*.

When $d(u_i, u_j)$ becomes smaller, it means that the two examples are more similar. Equation (4) expresses the prediction that will be the class, and that has the most members in the kNNs

$$y\ (d_i) = \arg\max \sum_{u_j \in \mathrm{NN}} y\,(u_j, c_k) \tag{4}$$

where
- d_i text example;
- u_j one of its kNN in the training;
- u_j, c_k indicates whether u_j belongs to class c_k.

B. Reuse

In the reuse task, a solution is obtained from the retrieved cases. In order to enable to arrive at a value, (5) is used. According to [51], this is called hypothesis fitness, and assumes that the electricity reduction R of specific case j can be formulated by appropriately weighting its attributes, as

$$R_j = w_1\ x_1 + w_2 x_{j2} + w_3 x_{j3} \cdots + w_i x_{ji}. \tag{5}$$

Applying this relation to the set of cases obtained through the retrieved process, can be performed as

$$\begin{bmatrix} x_{11} & \cdots & x_{1i} \\ \vdots & \ddots & \vdots \\ x_{j1} & \cdots & x_{ij} \end{bmatrix} \cdot \begin{bmatrix} w_1 \\ \vdots \\ w_i \end{bmatrix} = \begin{bmatrix} R_1 \\ \vdots \\ R_j \end{bmatrix}. \tag{6}$$

Equation (7) performs the matrix transformations where the vector of electricity reduction passes to the first member. In this equation, the matrix multiplication between the variable of each case with the weight of each variable subtracted from the electric reduction is equal to a certain error e_j

$$\begin{bmatrix} x_{11} & \cdots & x_{1i} \\ \vdots & \ddots & \vdots \\ x_{j1} & \cdots & x_{ij} \end{bmatrix} \cdot \begin{bmatrix} w_1 \\ \vdots \\ w_i \end{bmatrix} - \begin{bmatrix} R_1 \\ \vdots \\ R_j \end{bmatrix} = \begin{bmatrix} e_1 \\ \vdots \\ e_j \end{bmatrix}. \tag{7}$$

Equation (8) is an objective function that has the main goal of minimizing the sum of square root of the error e_j. The optimal combination of weight will be obtained when the function reaches a minimum value, which is gained by solving each one of the equations resulting from the matrix calculation. The number of equations will be equal to the number of retrieved cases

$$\min f\ (e) = \sqrt[2]{\sum\nolimits_{\max j}^{j=1} (e_j)^2}\ . \tag{8}$$

For solving (8) and finding the ideal solution for combination of weights to minimize the equation, SVM are used [52]. The information used in the SVM follows the following format:

$$(y_1, x_1)\ ,\ \ldots,\ (y_1, x_1)\ , x \in R^n, y \in R \tag{9}$$

where each example $x_{\rm i}$ is a space vector example; y_i has a corresponding value; n is the size of training data. For classification: y_i assumes finite values; in binary classifications: $y_i \in \{-1, +1\}$; in digit recognition: $y_i \in \{1, 2, 3, 4, 5, 6, 7, 8, 9, 0\}$; and for regression purposes, y_i is a real number ($y_i \in R$).

The radial basis function (RBF) is used as kernel function, with a Gaussian function of the form

$$K\ (x, y) = e^{\left(-\frac{(x\ -\ y)^2}{2\sigma^2}\right)}\ . \tag{10}$$

Classical techniques utilizing RBF employ some method of determining a subset of centers. Typically a method of clustering is first employed to select a subset of centers. A smart feature of the SVM is that this selection is implicit, with each support vectors contributing one local Gaussian function, centered at that data point. By further thoughts, it is possible to select the global basis function width, or angle (σ) using the structural risk minimization principle [53].

C. Revise

In this paper, the revise task is formulated from the existing knowledge about the problem. It replicates an expert system [19], which intends to emulate in CBR the decision-making ability of a human expert. For this purpose, the rules presented in this section have been created, which are applied to the solution obtained by the reuse task. The main target of the created rules is variable x_3 representing the hour of the day. In (11), if the result of reuse task ($CRreuse$) is less than zero, the result of the revise task ($CRrevise$) will be zero

$$\text{if } CRreuse < 0\ \rightarrow CRrevise\ =\ 0. \tag{11}$$

Equation (12) defines the rule for the hours between 0 and 5. In this rule, it is imposed on the system that at least there must be $Cmin$ kW of consumption, and reduce the remaining by half. x_8 indicates the electric consumption in this and other equations

$$\begin{aligned}&\text{if } x_3 \geq 0\ \cap\ x_3 < 5\\ &\qquad \cap\ (CRreuse\ =\ 0\ \cup\ x_8 > Cmin)\\ &\qquad \rightarrow CRrevise\ =\ \frac{x_8 - Cmin}{2}.\end{aligned} \tag{12}$$

Equation (13) represents the meal hours. At this time, the reduction should be 25% of the value corresponding to the load x_8, less the production itself, represeting by x_9 in the equations

$$\begin{aligned}&\text{if } \Big((x_3 > 7.3\ \cap\ x_3 < 9\Big)\\ &\qquad \cup\,(\,x_3 > 12\ \cap\ x_3 < 13.3)\\ &\qquad \cup\,(\,x_3 > 19.3\ \cap\ x_3 < 21)\Big)\\ &\qquad \cap\,\Big(CRreuse\ =\ 0\ \cup CRreuse\\ &\qquad > x_8 - x_9\Big) \rightarrow CRrevise\\ &\qquad =\ 0.25 \times (x_8 - x_9)\,.\end{aligned} \tag{13}$$

Equation (14) represents the hours between the breakfast and lunch, and from lunch to dinner. x_7 represents the number of inhabitants, which is taken into account by this rule, and if it is less than 3, the value of the reduction will be half of the consumption, to which the production is substracted; otherwise the reduction will be a quarter

$$\begin{aligned}&\text{if}\Big(\big(x_3 > 9 \cap x_3 < 12\big) \cup (\,x_3 > 14\ \cap\ x_3 < 18)\Big)\\ &\qquad \cap\,(CRreuse\ =\ 0 \cup CRreuse\\ &\qquad > x_8 - x_9)\\ &\qquad \text{elseif } x_7 < 3 \rightarrow CRrevise\ =\ \frac{x_8 - x_9}{2}\\ &\text{else } CRrevise\ =\ \frac{x_8 - x_9}{4}\ .\end{aligned} \tag{14}$$

Equation (15) represents the hours between 21 of the current day and 0 of the next day. The value of the reduction is half of the load minus the production, however, it is expected that the residential production in this schedule is around zero

$$\begin{aligned}&\text{if } x_3 > 21\ \cap\ x_3 < 0\\ &\qquad \cap\,(CRreuse\ =\ 0 \cup CRreuse\\ &\qquad > x_8 - x_9) \rightarrow CRrevise\\ &\qquad = \frac{x_8 - x_9}{2}\ .\end{aligned} \tag{15}$$

Equation (16) represents the hours between 5 and 7.3, and it is defined so that 24 h are all covered. This rule indicates a reduction of 10% in all consumption above the minimum standard consumption $Cmin$

$$\begin{aligned}&\text{if } x_3 > 5\ \cap\ x_3 < 7.3\\ &\qquad \cap\,(CRreuse\ =\ 0 \cup x_8 > Cmin)\\ &\qquad \rightarrow CRrevise\\ &\qquad =\ 0.8 + 0.1 \times (x_8 - Cmin)\,.\end{aligned} \tag{16}$$

At the end of this task, when all defined rules are applied to the results of the reuse task, the revised value will be obtained.

D. Retain

This is the last task of the cycle, which decides if the new case should or not be incorporated in the DB. For this goal, (17) and (18) are expressed as

$$\frac{|\mathrm{SHIM}_{\mathrm{result}} - \mathrm{CR}_{\mathrm{result}}|}{\mathrm{SHIM}_{\mathrm{result}}} \leq 0.2. \quad (17)$$

In (17), one of the conditions that the new case should respect to be incorporated in the DB is represented. If the difference between the SHIM result and the CBR result is greater than 0.2, the new case will be excluded, since it does not represent a good enough solution (the error is too big)

$$\begin{array}{c} Similarity\,\{new\ case,\ best\ similar\ case\ in\ DB\} \\ \leq 95\% \end{array} \quad (18)$$

According to (18), only new cases with a similarity smaller than 95% relatively to the most similar case within DB will be accepted in DB. This is defined so that the DB is not be filled with a numerous number of very similar cases, which do not added new valuable information. If these two conditions, (17) and (18), are true, the new case is incorporated in the DB.

V. Case Study

This section describes the case study, which demonstrates the performance of the proposed methodology. This section is divided into three sections. Section V-A is used to demonstrate the performance of the CBR recommender system, comparing the CBR results to the reference results (real reduction). A DB with 84 real cases of house consumption, modeled by the characteristics presented in Table II, is considered. These cases represent different situations regarding the time of day, number of people in the house, season, etc. Five different values of k are used on k-NN: all cases in DB, 10, 5, 3, and 1 most similar cases, so it is possible to assess the relationship between the number of considered similar cases and the final result. In these experiments, the results of the SVM approach are compared to the results of a previous particle swarm optimization (PSO)-based implementation. The considered PSO approach implements an optimization method, which optimizes (8) in order to achieve as output the value of w_{i}. Once the SVM and PSO are executed, the achieved values of importance for each variable are applied to the new considered case and the final result is obtained. The new considered case is an already existing case in the DB, which is not considered in the learning process. In this way, it is possible the compare the real value of this case with the reduction values resulting from the proposed approach.

Section V-B validates the CBR performance using a new case, which is new and is not previously stored in the DB. The objective is to assess the applicability of the proposed approach to a completely new case that emerges in the future.

Finally, Section V-C demonstrates the application of the recommendations provided by the proposed CBR model in the house energy management performed by SHIM. As explained previously, SHIM is a house energy management system that enables optimizing the energy consumption of a house taking into account the required levels of reduction. In this way, considering the energy reduction value provided by the proposed method, SHIM determines in which devices the reduction should act. The CBR review phase establishes the final restrictions that limit the final reduction value to the extent in which the user's comfort is not affected.

TABLE III
Profile of Subject Cases for Model Validation

Variables	Case 1	Case 2	Case 3	Case 4	Case 5
x_1	7	1	1	7	7
x_2	1	8	5	10	10
x_3	2.45	9.3	12.15	18.45	23.45
x_4	3	1	4	2	2
x_5	11.2	17.5	20.7	20.2	20.6
x_6	95	86	66	89	67
x_7	4	4	4	4	6
x_8	0.6	0.12	3.211	3.435	2.413
x_9	0	0.98	1.6	0.125	0
x_{10}	0.1634	0.1634	0.1634	0.1634	0.1634
R_{real}	0	0	0	0.05	0.09

TABLE IV
Performance Results

Number of NN	SVM		PSO	
	RMSE	Time (s)	RMSE	Time (s)
All Cases	0.179456127	1.726838	0.0601422	99.061688
10	0.208943947	1.672306	0.0658977	87.227735
5	0.211000938	1.696885	0.051008	85.543639
3	0.192366911	1.659253	0.0437255	84.420653
1	0.191951334	1.706994	0.0311592	63.824565

A. CBR Performance

In order to demonstrate the applicability of the proposed methodology, five cases were chosen randomly in the DB, as presented in Table III. In this way, it is possible to compare the resulting value of the CBR and the real value.

With the set of five cases shown in Table III, five different approaches were chosen, which vary in the number of neighbors selected by the k-NN approach. Initially, when the CBR is initialized, the number of neighbors to be selected is one of the input variables.

Table IV shows the results for the following number of neighbors: all cases of the DB, ten more similar cases, five, three, and one more similar cases. In order to obtain a comparison, the results of another methodology applied to the same problem are presented, namely using the PSO [54] to obtain the reuse value in the CBR cycle. The SVM uses the number of selected similar cases selected by the k-NN as training data. After the training process, a trained model is generated and applied to the case to be evaluated and the solution is obtained.

As can be observed from the obtained results, the RMSE obtained in each of the scenarios is very similar, although when the model selects all the cases of the DB, the error shows a decrease. This is an indication that the SVM needs a lot of training data to be efficient. When compared to the PSO error results, the PSO results in slightly lower values; however, by comparing the runtime values of the entire CBR system using

TABLE V
ERROR RESULTS FOR ALL CASES

Cases	CR-reuse	CR-revise	real	$\|Error\|$
case 1	0.010265	0.010265	0	0.010265
case 2	-0.03385	0*	0	0
case 3	0.067536	0.4*	0	0.4
case 4	0.077715	0.077715	0.05	0.027715
case 5	0.077792	0.077792	0.09	0.012208

*Values with revise.

TABLE VI
SIMILAR CASES SELECTED FOR CASE 1

k	Index of case
All cases	All cases in data base
10	$\{1, 10, 12, 15, 21, 31, 48, 49, 55$ *and* $57\}$
5	$\{1, 10, 12, 15$ *and* $48\}$
3	$\{10, 15$ *and* $48\}$
1	$\{15\}$

TABLE VII
DESCRIPTION OF NEW CASE

Variables	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	R_{real}
New Case	3	7	19	1	14	85	4	1.779	0.05	0.1634	-

SVM and PSO, as can be seen from Table IV, the SVM values are much smaller. This is crucial for the recommender system, since recommendations have to be delivered in real time to the house users.

Table V shows the results for the case where all the cases of the DB are used as training data in the SVM.

From the analysis of Table V, one can observe that there are cases in which the values resulting from the reuse step have undergone changes in the review step, namely case 2 and 3. In case 2, the reuse value was less than zero, and in the revision step, it has been set to 0. In case 3, the set of variables of the case study indicates that it belongs to a specific interval for which revision rules are created; in this way, the value is changed. In Table V, the value of the error is calculated as a function of the value obtained in the review step.

In Table VI are presented the cases selected for case 1. The presentation of these results allows us to explain the operation of the *k*-NN. *k* indicates the number of similar cases to be selected by the *k*-NN. This algorithm selects the closest cases according to the calculation of the Euclidean distance. As one can see, the most similar case to case 1 is identified with index 15. The most similar cases to case 1 are repeated along the respective sets.

B. CBR Validation

This section presents a validation case for a new case where there is no real value. The variables that characterize the new case are presented in Table VII.

The new case concerns a Wednesday on summer, more precisely a day of July at 7 P.M. There was at this time an outside temperature of 14 °C and a humidity of 85%. One hour after dinner at the house were four people consuming approximately 1.8 kW, output from external sources (solar) is 0.05 kW, which was to be expected as it is at the end of the day.

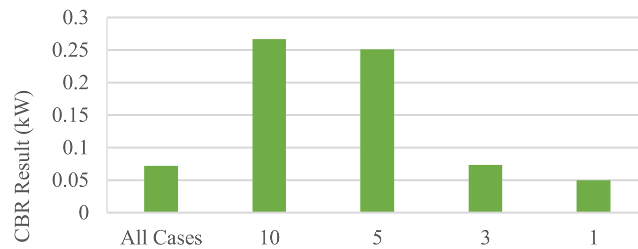

Fig. 2. CBR results for different NN.

Figure 2 presents the results obtained by the CBR system. As can be observed, there are different values of recommended reduction depending on the different numbers of neighbors selected by the *k*-NN.

As can be seen from Fig. 2, there are two sets of more probable values. As can be seen, when using all cases for training of the SVM model, 3 or 1, the result of the CBR is approximately 0.06 kW. On the other hand, if ten or five cases are used as training values for the SVM, the output of the CBR is approximately 0.26 kW.

C. Application in SHIM

From the achieved results, it is possible to recommend the reduction of consumption to consumers. It is true that the greater the reduction, the greater the monetary value is saved, but it may be impossible to reduce the maximum value since it may influence the comfort of the user of the house.

In order to analyze the impact of the recommendation suggested by the proposed CBR system, the results of the CBR model are applied in SHIM. In this way, it is possible to see the actual change in consumption, resulting from the suggested reductions. Using the MAS society presented in Section III, with the interactions shown in Fig. 3, an aggregator agent from the MASGriP system sends a request for energy reduction to the considered house. The CBR agent executes the proposed methodology and then communicates the results to the IDeSMAS system. IDeSMAS uses its agents to collect the necessary contextual information, and uses the respective agent to execute SHIM. Once the devices consumption scheduling is defined by SHIM according to the reduction provided by the proposed CBR approach, results are communicated to another member of the MAS society: the PLCMAS. This system then actually implements the required reduction and establishes the required consumption level in the different devices of GECAD's laboratory controlled home by using the different agents that control the different devices. All this interaction, setting is defined and specified using TOOCC.

Fig. 4 shows the total consumption of the considered house throughout the 24 h of the considered simulation day—same day as the case of Table VII. In order to recommend a reduction value for the entire day, the CBR model is executed for each 5 min, considering all cases as training for the SVM, as it has been concluded from Section V-A that this is the solution that results in the minimal error. Given the results of the CBR method,

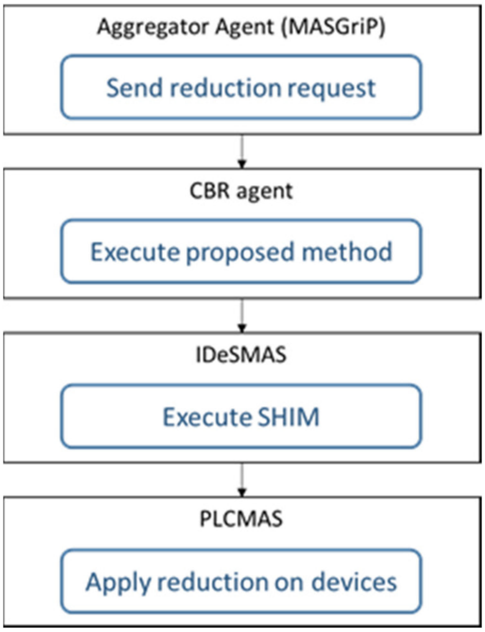

Fig. 3. Sequence of agents' interaction.

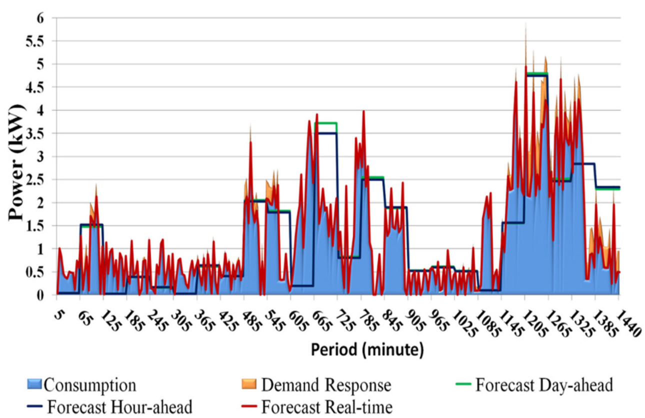

Fig. 4. Total consumption of the house throughout the considered day and DR reduction amount resulting from the proposed methodology.

Fig. 4 also shows the amount of consumption reduction that is suggested by the proposed methodology throughout the day.

From Fig. 4, it is visible that some amounts of reduction (identified as DR in the figure) are suggested by the proposed methodology to some periods of the day, especially during the peak hours of consumption. Fig. 5 shows the results of SHIM when applying the reductions resulting from the proposed method to the several devices of the house. The red line represents the consumption limit resulting from the proposed methodology to be applied by the ERM performed by SHIM. Hence, all consumption values above the line are amounts being reduced.

From Fig. 5, it is visible that SHIM scheduled the consumption of several devices according to the reduction values provided the proposed methodology. It is noteworthy that SHIM considers the users comfort in the energy resources optimization process. Hence, values of reduction that would cause a significant impact on users' comfort are not applied. As can be seen from the achieved results, SHIM has been able to apply

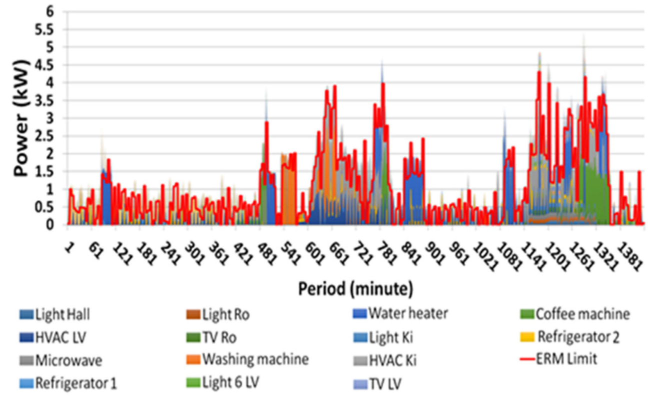

Fig. 5. Consumption per device of the house throughout the considered day and reduction applied to each device.

all the reductions that are recommended by the CBR, hence validating the adequacy of the proposed method results.

VI. Practical Implications

These case study results show that the proposed approach is able to provide adequate recommendations for the amount of energy to be reduced in an energy management context. The application of this methodology in the field requires only that a communication channel is installed between the customer and the manager/operator.

From the aggregator perspective, the requirements for putting the proposed approach into practice are simply the access to the log of previous cases for analysis, and also the access to the information that characterizes a new case. On the customer side, besides the communications to enable the flow of information, there are no barriers to the implementation of the proposed approach. The methodology results in a recommendation, which is sent to the building; hence, the results are not dependent on the way these recommendations are applied by the customer. They can be applied by means of automatic BEMS, such as SHIM, or they can be applied manually by the user. Either way, the proposed approach is not dependent on the actual control.

The main limitation of the proposed approach is the need for an updated log of past cases, so that these can be used for the learning process. Without such log, it is not possible to execute the proposed method. However, as mitigation measures, the log of previous cases from similar buildings can be used in the starting point of the learning process, being adapted over time. Also, still with the support on information of similar buildings, the proposed CBR method can be extended to include an analogy learning component [55].

In terms of economical and regulatory issues, there are currently no constraints that prevent the proposed approach from being applied. However, the current DR and flexibility trading regulations are still not open enough to potentiate a widespread of such approaches [6], [8].

VII. Conclusion

This paper proposes a multi-agent-based CBR recommender system for intelligent energy management in buildings. The proposed methodology is used to recommend the ideal amount of reduction in buildings' consumption, according to the history of previous similar cases of reduction applied in similar contexts. The proposed approach is integrated in a society of MAS, directed to the study and simulation of power and energy systems, and enables the connection between the building and the external system. The developed model uses the *k*-NN clustering algorithm to identify the most similar cases, which are then combined using an SVM approach. An *ad hoc* expert system is applied to refine the achieved results according to an *a priori* defined set of rules.

Results show that the proposed methodology is able to determine suitable amounts of consumption reduction based on previous cases, as demonstrated by their application in the SHIM BEMS. The reduction can be applied without affecting the users' comfort, and thus can prove to be a suitable solution for integration in complex energy systems. Moreover, the comparison of the SVM with a PSO implementation shows that, although the PSO is able to achieve slightly lower errors, the SVM approach is capable of reaching similar results in a much faster execution time. Hence, the SVM approach is suitable for real application scenarios, where recommendations must be done in near real time.

As future work, different methodologies to manage the reuse phase will be applied and compared, namely artificial immune systems and simulated annealing, aiming at achieving solutions with lower error in faster execution times.

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Ricardo Faia received the B.Sc. degree in electrical engineering from the Polytechnic of Bragança, Bragança, Portugal, in 2013, and the M.Sc. degree from the Polytechnic of Porto, Porto, Portugal, in 2016. He is currently working toward the Ph.D. degree at the University of Salamanca, Salamanca, Spain.

He is also a Researcher with GECAD research group, Polytechnic Institute of Porto, Porto, Portugal. His research interests include electricity market negotiations, case based reasoning, meta-heuristic optimization and smart energy grids.

Maria Navarro-Caceres received the Ph.D. degree in computer science from the University of Salamanca, Salamanca, Spain, in 2017.

She is currently a Researcher with the BISITE research group, University of Salamanca. Her research interests include agent-based systems, case-based reasoning, and metaheuristic optimization.

Gabriel Santos received the bachelor and M.Sc. degrees in informatics from the Polytechnic Institute of Porto, Porto, Portugal. He is currently working toward the Ph.D. degree at the University of Salamanca, Salamanca, Spain.

He is also a Researcher with GECAD, Polytechnic Institute of Porto, Porto, Portugal. His research interests include multi-agent systems, ontologies, electricity market negotiations, decision support systems, and smart energy grids.

Juan Manuel Corchado received the Ph.D. degree in informatics with Universidad de Salamanca, Spain, in 1995 and the Ph.D. degree in artificial intelligence with the University of the West of Scotland, UK, in 1998. He is the Vice-rector of the University of Salamanca, Salamanca, Spain, for research and innovation. He is also the Director of the BISITE research group and of the University of Salamanca Scientific Park, Salamanca, Spain. His main research interests concern artificial Intelligence applications to multiple domains, including energy systems, robotics, and communications.

Tiago Pinto (M'15) received the B.Sc. and M.Sc. degrees from the Polytechnic Institute of Porto, Porto, Portugal, in 2008 and 2011, and the Ph.D. degree from the University of Trás-os-Montes e Alto Douro, Vila Real, Portugal, in 2016.

He is also a Researcher with the BISITE research group, University of Salamanca, Salamanca, Spain. His research interests include multiagent simulation, machine learning, automated negotiation, smart grids, and electricity markets.

Zita Vale (S'86–M'93–SM'10) received the diploma degree in electrical engineering and the Ph.D. degree, both from the University of Porto, Porto, Portugal, in 1986 and 1993, respectively.

She is currently the Director of GECAD and a Professor with the Polytechnic of Porto, Porto, Portugal. Her main research interests include artificial Intelligence applications to power system operation and control, electricity markets, and distributed generation.