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A Fuzzy-Based Building Energy Management System for Energy Efficiency †

José L. Hernández [1], Roberto Sanz [1,*], Álvaro Corredera [1,*], Ricardo Palomar [2] and Isabel Lacave [3]

1 Fundación CARTIF, Energy division, 47151 Boecillo, Spain; josher@cartif.es
2 Acciona R+D, 41012 Sevilla, Spain; ricardo.palomar.calahorra.ext@acciona.com
3 Acciona Construcción, 28108 Madrid, Spain; isabel.lacave.azpeitia.EXT@acciona.com
* Correspondence: robsan@cartif.es (R.S.); alvcor@cartif.es (Á.C.); Tel.: +34-983-548911 (R.S. & Á.C.)
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Abstract: Information and communication technologies (ICT) offer immense potential to improve the energetic performance of buildings. Additionally, common building control systems are typically based on simple decision-making tools, which possess the ability to obtain controllable parameters for indoor temperatures. Nevertheless, the accuracy of such common building control systems is improvable with the integration of advanced decision-making techniques embedded into software and energy management tools. This paper presents the design of a building energy management system (BEMS), which is currently under development, and that makes use of artificial intelligence for the automated decision-making process required for optimal comfort of occupants and utilization of renewables for achieving energy-efficiency in buildings. The research falls under the scope of the H2020 project BREASER which implements fuzzy logic with the aim of governing the energy resources of a school in Turkey, which has been renovated with a ventilated façade with integrated renewable energy sources (RES). The BRESAER BEMS includes prediction techniques that increase the accuracy of common BEMS tools, and subsequent energy savings, while ensuring the indoor thermal comfort of the building occupants. In particular, weather forecast and simulation strategies are integrated into the functionalities of the overall system. By collecting the aforementioned information, the BEMS makes decisions according to a well-established selection of key performance indicators (KPIs) with the objective of providing a quantitative comparable value to determine new actuation parameters.

Keywords: building energy management system (BEMS); monitoring and control; data analytics; key performance indicators (KPIs); decision-making tools; fuzzy logic; artificial intelligence

1. Introduction

As it is stated in the European Commission Energy 2020 Strategy, “Energy is the life blood of our society (. . .). Europe cannot afford to waste energy” [1]. One of the greatest challenges Europe is currently facing is how to provide citizens and industries with safe, secure, sustainable, and affordable energy. “The European Council adopted in 2007 ambitious energy and climate change objectives for 2020—to reduce greenhouse gas emissions by 20%, rising to 30% if the conditions are right, to increase the share of renewable energy to 20% and to make a 20% improvement in energy efficiency by 2020” [1]. Energy efficiency is one of the central objectives for 2020 in the European Union (EU), as well as a key factor in achieving the long-term energy and climate goals. Energy efficiency is the most cost effective way to reduce emissions, improve energy security and competitiveness, and make energy consumption more affordable for consumers [1]. The current building stock of the EU has enormous potential for improvement of its energy efficiency and the application of renewable energy sources

(RES). The transformation of that building stock into energy-efficient buildings is therefore imperative to the objectives established in the European 2020 strategy [1].

The purpose of this paper is to show how information and communication technologies (ICT) cannot be neglected in reaching Europe's 2020 strategy by implementing a building energy management systems (BEMS) that can be used to balance various energy sources, facilitate renewables uptake, and ensure energy efficiency at a scalable building level. A building's envelope is the key element to address in order to significantly increase the energy efficiency and the use of RES in the building sector. Thus, The BRESAER (BREakthrough Solutions for Adaptable Envelopes in building Refurbishment) project [2] aims to turn the building envelope into an active element rather than a passive one, meeting more functions than just the separation of the exterior from the interior with insulation, and therefore enabling it to adapt to a dynamic environment and to building occupants requirements during its lifetime. However, this new active envelope system needs to be governed with ICT, and a BEMS with advanced prediction capabilities is the optimal means to balance the associated energy sources in an optimized way. It measures and controls both the envelope's active components and related energy consuming devices using integrated, simulation-based control techniques for automating the establishment, and monitoring of optimal energy-related operational plans for a building.

In the last decade, there has been very intensive research conducted about control strategies for building management, but there are still some open questions to be answered. For instance, unlike traditional control methodologies, new trends suggest the importance of including models to predict building occupants' behavior [3]. Some researchers have opted for including key parameters such as energy costs [4], or extra information related to the building extracted from building information modelling (BIM) applications [5]. More complex BEMS solutions, however, are dedicated to model-predictive controllers, for example where building models and behavioral equations are integrated to improve the overall energy performance of the building [6,7].

2. State of the Art in Control Systems for Buildings

Nowadays, two distinguishable types of BEMS products exist: commercial products, and those developed in or for research-oriented activities. By way of a market analysis, some current examples of commercial products have been summarized in Table 1 [8]. Basically, the main functionalities of these three commercially available BEMS products are limited to energy monitoring and reporting on energy consumption within a given building.

Table 1. Comparison of three commercial examples for BEMS solutions.

Feature	Smarkia [9]	NETxAutomation [10]	OpenDomo [11]
Multiprotocol	yes	yes	yes *
Automated reports	yes	yes	yes
Data analysis (KPI)	yes	no	no
Internet of things	no	yes	no
Advanced control	yes **	no	no

* with limitations, ** based on basic rules not actually advanced.

In terms of research-oriented BEMS studies, as mentioned in the introduction, there are many articles outlining diverse and multiple approaches to the trend of model-predictive control for energy management in buildings [3–7], which in fact represent the declarative state of the art for the BEMS field. However, it should be noted that there are other approaches that try to include more parameters thanks to the monitoring networks of buildings. Even more, the influence of the human behavior of the occupancy is being included in the loop and has become imperative for advanced BEMS solutions to achieve notable market uptake results.

Improvements with Respect to Comparative Research

As mentioned, the current state of the art for BEMS tools is model-predictive energy controllers. In fact, a comprehensive literature review performed by BRESAER has uncovered that there are several commercial works and research lines trying to get better results in terms of energy efficiency with the use of advanced systems and artificial intelligence in a BEMS. The real challenges of these approaches for a BEMS are the algorithmic programming complexity and high costs of implementing the model-based control across differing building stock requirements. That is the reason why the market is still dealing with rule-based controllers, which, in spite of being functional, provide less overall accuracy in achieving renewables integration, occupant comfort, and energy savings.

Within BRESAER, designing the building model is based on both the BEMS platform architecture and the stock-specific simulation approach, with each being implemented under a three-level framework (explained below), aiming at reducing the complexity and, therefore, the costs. Furthermore, this multimodal framework does not affect the accuracy of the BEMS because through calibration and validation methods based on real data, the accuracy is ensured and scalable for various building typologies. In this way, the BRESAER BEMS employs a "just enough accurate" model, deployed with particular focus on the relationship between complexity and accuracy.

There is evidence of a BEMS solution that endeavored to simplify the model [7] in a similar fashion to the simplification of the complexities in the BRESAER BEMS. However, their specific intention in this case was to implement a mathematical model representing the thermal behavior of the building, with the resultant BEMS model being even more complex than necessary. Additionally, one BEMS solution studied in the state of the art review implemented co-simulation models representing the current status of the building in a very accurate manner [6], but failed to incorporate advanced prediction algorithms. As such, the potential market impact of the BEMS solution being developed by BRESAER is higher in comparison due to the prediction functionality and the focus on thermal comfort while facilitating RES penetration. While the aforementioned research ran on-the-fly simulations, the BEMS of BRESAER runs predictive simulations being able to anticipate the thermal behavior of the building and, hence, increase the thermal comfort of occupants and overall energy-efficiency at a building level through greater accuracy of the controller.

Moreover, the BRESAER BEMS solution is able to predict the renewable contribution of the energy sources in a building thanks to the integration of cutting-edge solar estimator technologies. Weather forecast services are usually not providing solar radiation estimation, but this variable is important when analyzing solar thermal systems. In this way, the BRESAER BEMS integrates a novel solar estimator taken from existing deployments of solar trackers. The great advantage of adopting the BRESAER BEMS for energy managers is the maximization of renewable contributions based on predictive values and building energy models.

Finally, with regard to other BEMS research studies in the literature review, the influence of the occupants' comfort levels is included into the control mechanisms, although it should be taken into account that their behavior is unexpected [3]. Therefore, within BRESAER, artificial intelligence is included in the BEMS algorithms and, in particular, fuzzy logic that minimizes these parametric uncertainties. In this case, these user behavior models generated by the BRESAER BEMS may be compared with the actual behavioral data produced by the occupants to create an accurately monitored energy model and consumption profile of the building for end-using energy managers to effectively control the building's thermal performance.

3. BEMS Architecture Developed by BRESAER

As stated, BRESAER advances the state of the BEMS arts with a more accurate energy management system that utilizes model-predictive behavior of building occupants, allowing energy managers to better monitor and control their building's assets. For this purpose, the design process of the BRESAER BEMS started with the collection of the (non) technical requirements and use cases [8] according to the targets of the project (i.e., improve the energy efficiency and the comfort levels of occupants). Next, the high-level BEMS architecture was defined according to the use cases analyses and requirements prioritization, as displayed in Figure 1 [8], which is an illustration of the multi-layer framework.

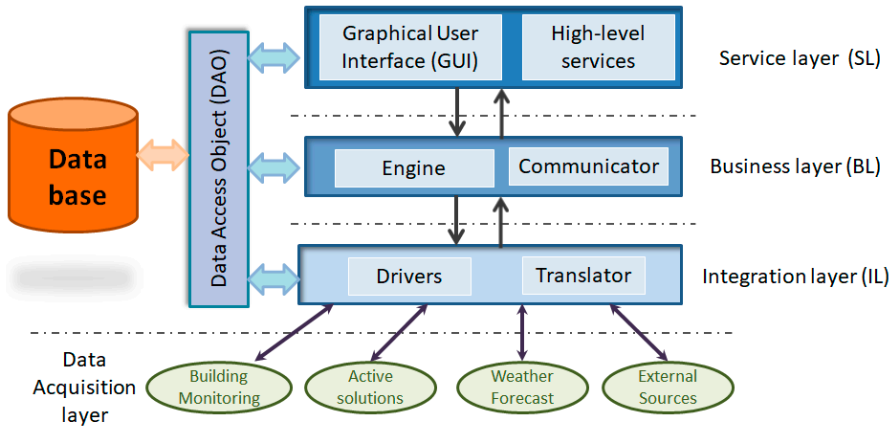

Figure 1. BRESAER BEMS system architecture.

The data acquisition layer highlights the categories of real data collected on a periodic basis in order to obtain a historical data record. This data gathering process allows for performing the final analysis of predicted user behavior, as well as applying the control strategies by means of the self-learning methodologies. Several data resources were identified in the BRESAER demonstration activities: Firstly, data from an on-site building monitoring system (BMS) that represents the sensor network installed in the building (thermal comfort and energy consumption metering). Secondly, the active solutions refer the active generation facilities existing in the building (e.g., boiler) and the new ones (e.g., solar thermal air system) so as to balance the energy loads. Moreover, the weather forecast needs to be taken with the objective of predicting the indoor climate conditions, thus making it possible to preemptively determine the actuation parameters (control variables) according to the future outdoor climate predictions. Additionally, other sources can also be taken into consideration if necessary for the building's energy management goals.

The integration layer (IL) has an objective to connect the disparate data sources, merge the information when needed (e.g., periodic data gathering and storage once in the database), and ultimately harmonize data samples into the same format. The business layer (BL) is dedicated to the main activities of the BEMS, i.e., communication between modules, accessing the database, and providing data to the high-level services, among others. Basically, it includes some intelligence in terms of communication; it knows the modular deployment schema and, therefore, how to optimally exchange modular information.

The services layer (SL) is in charge of the BEMS intelligence in terms of control. The module named 'Services' contains the control algorithms, self-learning components, prediction tools, and connectors to the simulation engine. Moreover, this layer includes the visualization of the information regarding both monitoring and control parameters.

Last but not least, the data access object (DAO) is a cross-cutting vertical layer which has the goal of ensuring connection to the database. The added value of this layer is the capability of interfacing between the objects world (e.g., Java programming language) and the database format (relational).

4. Fuzzy-Based Control Techniques

BRESAER takes a scenario-based approach to the design of control strategies. There are five use cases [12] used to validate development of the BEMS, three related to the solar thermal air system, and two related to the windows:

- Solar thermal air system-related use cases:

  1. Winter thermal production thanks to the solar thermal air system, which aims at thermal energy generation during winter to avoid the use of the existing facilities through the injection of air into an air handling unit (AHU).
  2. Passive cooling in order to take advantage of the celestial phenomenon of black body to cool the rooms. This phenomenon is basically how solar panels may be used to catch night radiation to cool the rooms.
  3. Summer thermal production, similar to winter but with the difference that the AHU is able to use the hot air and convert it into cold air.

- Window-related use cases:

  4. Thanks to the blinds, the temperature inside the rooms may be controlled. That is to say, it is unavoidable that the solar gains increase the indoor temperature. Therefore, by means of opening/closing these blinds, the gains may be managed in order to increase them when it is cold inside or vice versa. It is important to note that the blinds may be positioned at multiple angles in order to reflect the sun's rays and manage these gains.
  5. Control of the lighting inside the rooms by managing the daylight penetration. This control scenario is complementary to the previous one.

Three distinct technologies have been compared—neuronal networks, flow control, and fuzzy logic [13]—in order for BRESAER to select the most suitable one for the BEMS implementation. Neuronal networks are very well-known and it allows for modelling the behavior of a building. These networks simulate the biological neuronal networks with the objective of learning and making the most appropriate decision. However, a disadvantage of neuronal networks is the lack of data for training, because although a baseline is available, the solution to be included within the BRESAER project makes the building completely new with a new set of behaviors. Flow control is based on the energy flows that go from the generation systems to the demand side, passing through the distribution elements. This design determines the mathematical equations of these energy flows into the building. However, due to the characteristics of buildings, this technology has also been discarded because of the needs of independent thermal zones in order to avoid overheating or under-heating, which is not possible for inclusion into the BRESAER solution. On the other hand, fuzzy logic does not need data and it avoids mathematical models. Moreover, it is based on advanced rules according to the expertise of the designer, which makes it perfectly suitable for BRESAER and the BEMS design objectives. Besides, it provides a way to make decisions about optimal behavior according to certain comfort constraints [12,13]. Complementarily, it dampens the uncertainties due to the human interaction with the energy systems, as previously stated.

Having selected the ideal choice for the BRESAER BEMS decision-making tools, the design of the fuzzy control algorithm requires the definition of a set of inputs. Table 2 [12] gathers all the input variables that are useful for the control algorithm and the associated energy facility that is affected. The data-points come from the aforementioned multiple sources, which supports the decision-making process in concert with the monitored energy behavior of the building.

One of the key aspects in the design of a fuzzy control strategy is the so-called fuzzification process, which is the way to determine the ranges where the variable has one certain value, and the definition of the uncertainty groups (zones where two ranges are crossed). One example is illustrated in Figure 2 [12] where the indoor temperature is fuzzified. Five groups are set up according to the ASHRAE standard [14], and comfort is considered between 21 °C and 24 °C (21–23 °C in winter and 22–25 °C in summer). Moreover, taking into account the building occupants and BEMS end-users' experience, the uncertainty groups are classified with lower temperatures where the human feeling varies more than with higher temperatures. These uncertainty groups are pivotal at the time of deciding the probability of the situations (i.e., comfort, cold, hot ...). This fuzzification process is rendered for each one of the input variables of the system because they need to be interpreted under the probabilities problem [12].

Table 2. Input parameter of the fuzzy logic.

Input	Solar Air System [1]	Dynamic Windows	Boiler
Indoor temperature	X	X	X
Blind angle status		X	
Blind position status		X	
Radiation forecast	X	X	X
Energy demand	X	X	X
AHU status (fan)	X		
Indoor luminosity		X	
External luminosity		X	
Indoor occupancy		X	
Temperature forecast	X	X	X
Sky forecast	X	X	X
Solar angle		X	
Boiler status			X
Schedule	X	X	X
Blind remote/manual		X	
Inlet temperature	X		X

[1] Solar thermal chimney that heats the air inside thanks to PV panels in order to inject hot air to the building.

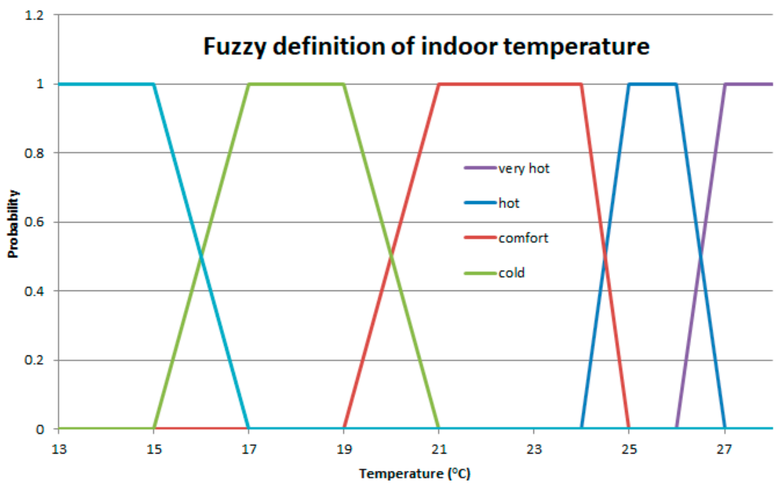

Figure 2. Fuzzification of the indoor temperature variable.

5. Prediction Tools

Fuzzy logic itself provides a set of advantages for decision-making tools—complemented with prediction—that is able to preemptively determine the behavior of the building with the aim of preparing the energy facilities to achieve the desired comfort levels. The great advantage of this technology above the other two that were compared, is the increase of accuracy in the control strategy and, thus, incremental energy savings by means of knowing the energy limitations and capabilities. Two basic prediction tools are used: simulation that provides information about the energy demand, and solar estimators that allows for determining the amount of energy in the solar air system. Both cases are fed with weather forecast services for achieving the forecasted indoor climate conditions, and integration within the control algorithm into the services layer.

5.1. Building Energy Performance Simulation

Building energy performance has two very distinguished pillars: control strategies and energy simulation models; both pillars are part of the developments to implement measures of energy efficiency into the BEMS control of buildings.

The control strategies are model based, i.e., make use of simulation results to obtain energy demand prediction of the building [12]. Hence, it is essential to establish a stable interface between the programming tools and the simulation engine. Nevertheless, the complexity requires, an iterative and incremental process for attaining simple simulation models with a reduced number of variables. They have been initially tested by BRESAER in order to continuously increase the complexity and scalability of the model (i.e., details of the building from a simple box to the integration of thermal zones and HVAC systems). The same is applicable from the point of view of control, where initially random values where generated and, at the end, real forecast data were used as input for the model.

Simulation models with different levels of complexity and accuracy have also been created for the BRESAER BEMS. As with the control strategies, they range from a very simple model based on a box with a single input variable, to a model that represents the building with HVAC systems in order to estimate the energy demand. This process permits checking the accuracy step-by-step in contrast with the response time. The reason is that the BEMS cannot run a simulation 'on-the-fly' whose duration would be extended for several hours. On the other hand, simplifying the model would affect the accuracy of the results. Hence, it is required to establish a trade-off balance between response time and accuracy ("just enough accurate"). Besides, the development of the simulation model is based on hierarchical approaches, where the different systems belong to a specified hierarchy. An example of this hierarchical approach is found in the prioritized categorization associated with the system, i.e., envelope, heating facilities, cooling facilities, energy generation, etc.

The simulation process has been divided into three different levels in order to achieve the objective of integrating a building energy performance simulation into the BEMS [12], as displayed in Figure 3 and explained below:

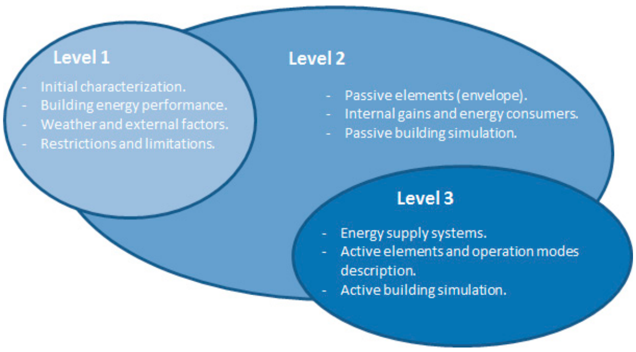

Figure 3. Three-level simulation approach.

- Level 1: To compile and analyze all information associated with the building energy performance. It is necessary to have a complete physical description of the building (envelope and construction properties), so as to acquire external weather information for a complete year (four seasons/year), and finally to detect the principal restrictions and limitations of the building and the environment that affects the simulation model (shadings, uses schedule, etc.).
- Level 2: To recreate the building into the specific simulation software module to define the building envelope and boundary conditions (location, geometrical, heat-mass transfer, windows, doors, shadings characteristics, etc.) with the objective of defining the real and actual building status.
- Level 3: To transfer the simulation model of the exemplary building typology to the main simulation engine environment in order to simulate the energy supply systems, including all

active elements and operation modes. As a consequence, this last level will obtain results for the complete energy model simulation of the building, aiming to maintain the comfort conditions inside the building (set-point temperatures).

5.2. Weather Forecast and Solar Estimator

As stated, the solar estimator prediction tool is used to determine the solar gains that the system will have in the short-term period (i.e., next hours). Nevertheless, the weather forecast services do not provide this information and additional techniques were implemented to mitigate that lack of data. In this case, solar tracker equations [15,16] have been used to obtain this estimation. Then, the solar hourly angle and radiation indicate the solar influence over the building. In order to calculate the solar tracker estimators, is was necessary to have the following inputs:

- Data with the level of clouds in the sky from the weather forecast. The measurement devices translate the value into percentile value from 0% (clear sky) to 100% (total cover).
- Time and date of the day that is the epoch in weather forecast services. For the iterations, and the instant values, it is necessary to know when the sky cover values are happening.
- Location of the destination. Longitude and latitude of the building.
- Height above sea level for pressure calculations.

The results of the implementation of this mathematical model are depicted in Figure 4 where the solar radiation estimation for the full year is illustrated at the first day of each month and at noon. Additionally, different sky cover percentages are used. The results clearly show how, even in the summer, when the sky is covered, the main contribution of the solar radiation is diffused (low values) and, for lower sky cover values, the trend is similar to the Gauss bell, which is the expected behavior.

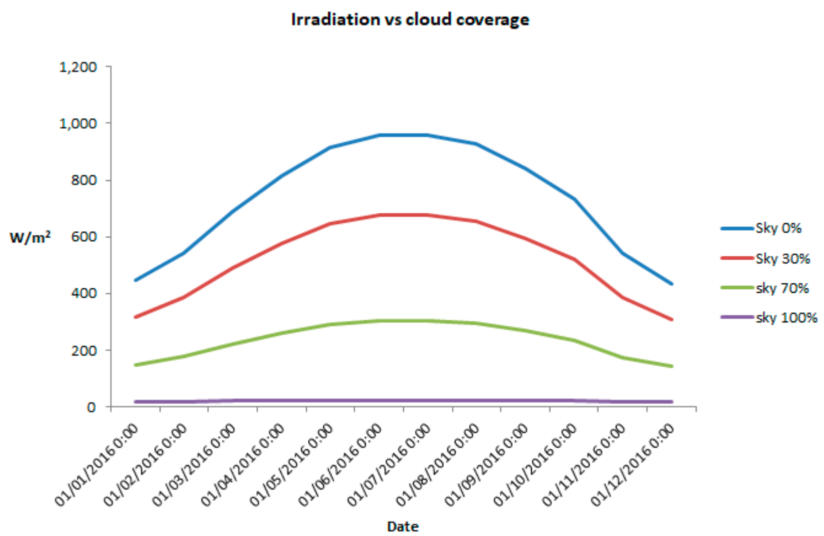

Figure 4. Solar tracker estimator results.

Both the weather forecast values and the solar tracker results are included as inputs for the simulation model, with the aim of obtaining the energy demand in the next time horizon (to be determined by the user), and the estimation of the 'available' energy from renewable sources.

6. Conclusions

BEMS solutions are a powerful tool that sometimes get neglected but allows efficient control and monitoring of the energy facilities of a building. Nevertheless, the current state of developments are still in experimental phases when speaking about artificial intelligence applied into buildings. It is true that some implementations are already being deployed based on neuronal networks and/or fuzzy logic, as well as on model-based management paradigms. However, the integration of prediction techniques such as those found in the BRESAER BEMS provides several advantages to the system when preemptively estimating the behavior of the building in order to make even more efficient use of the energy facilities in assuring the occupants' thermal comfort levels.

That is the reason why this paper has presented the design of a predictive model-based BEMS whose aim is the improvement of the energy efficiency and comfort levels by means of integrating advanced tools (e.g., artificial intelligence) while concurrently supporting RES penetration. The next steps for the BRESAER BEMS are its final implementation and deployment in order to validate and demonstrate its effect in a real environment. The main final objective of BRESAER is to determine the amount of energy savings that have been achieved with the fuzzy-based BEMS pilots and testbeds.

One of the advantages of the unique BRESAER system is the capability of adapting to different climatic properties, building stock typologies, and geographic locations as it uses the nearby weather services to make decisions depending on the region-specific climatic conditions. This feature increases its replicability to multiple countries and scalability to different building typologies. Moreover, another advantage is presented by the driver layer where a multi-protocol framework is implemented, being able to interface various HVAC systems. Hence, scalability of the BRESAER BEMS solution is ensured. Nevertheless, the challenge is due to the simulation model because it is building-dependent and, when deploying the solution in another building typology, its simulation model needs to be developed.

Author Contributions: The main work about design of the BEMS, control algorithms and solar estimators is done by José L. Hernández, Roberto Sanz and Álvaro Corredera. Ricardo Palomar and Isabel Lacave have focused their efforts on the simulation model and the automatic communication with the BEMS.

Conflicts of Interest: The authors declare no conflict of interest.

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