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Contextual Rule-Based System for Brightness Energy Management in Buildings

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Abstract: The increase in renewable generation of a distributed nature has brought significant new challenges to power and energy system management and operation. Self-consumption in buildings is widespread, and with it rises the need for novel, adaptive and intelligent building energy management systems. Although there is already extensive research and development work regarding building energy management solutions, the capabilities for adaptation and contextualization of decisions are still limited. Consequently, this paper proposes a novel contextual rule-based system for energy management in buildings, which incorporates a contextual dimension that enables the adaptability of the system according to diverse contextual situations and the presence of multiple users with different preferences. Results of a case study based on real data show that the contextualization of the energy management process can maintain energy costs as low as possible, while respecting user preferences and guaranteeing their comfort.

Keywords: building energy management; context awareness; renewable energy; rule-based systems

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1. Introduction

The energy crisis and the need for the decarbonization of the environment have encouraged the worldwide widespread integration of renewable sources into the power grid [1]. Drawing insights from experiences across different global regions reveals that the successful deployment of renewable energy sources hinges on tailoring approaches to the unique characteristics, needs and priorities of each country [2]. The prevailing market models for integrating distributed energy resources, exemplified by centralized models in the United States and decentralized models in Europe, serve as starting points [3]. The European Union, on one side, has taken proactive steps by formulating directives, policy guidelines and regulations to foster a progressively interconnected energy market. These measures empower consumers with a central, active role in the system [4]. In the United Kingdom, limitations persist in the participation of flexibility services and electricity transactions in local (peer-to-peer and distribution level) and national markets. Notably, restrictions are set in place for direct trading with consumers without supplier intervention, except in specific trial cases [5]. Australia is currently undergoing a series of reforms in its energy sector, building on its pioneer role in transitioning from central control to a market-based system. Projections indicate a substantial increase in wind and solar generation, leading to a shift from a 27% to over 48% renewables share by 2030 [6]. This shift prompts the need for urgent measures and new models for local dispatch and distribution grid-level generation–consumption balance. In South America, the dominance of hydropower in supplying large areas diminishes the necessity for locally managed electrical energy. However, the introduction of mechanisms to enhance the collaboration between hydropower and other renewables can optimize cost-efficiency and reliability in power systems [7]. Africa, endowed with abundant renewable energy sources, holds the potential to become a fertile region for renewable energy generation implementation.

Localized power grids or grid hubs, where energy is produced closer to the point of demand, align with Africa's renewable energy wealth [8]. In China and emerging Asian countries like the Philippines and India, significant changes are evident in electric power development. The construction of electricity markets in these regions is advancing steadily and rapidly compared to mature markets in the West [9].

Given the current global situation, a significant number of households already use renewable sources to meet their energy needs [10]. To improve the resource management capability in buildings, the concept of the Energy Management System (EMS) emerges. An EMS is described as a combination of strategies and methods to improve energy performance and efficiency [11]. EMS solutions can be single or multi-objective and their implementation can be carried out in different infrastructures such as a Building Energy Management System (BEMS), House Energy Management System (HEMS) or Factory Management System (FEMS), among others [12].

The intrinsic complexity of buildings results from the different users of the building and their different preferences and requirements. In this sense, several control strategies are proposed in the literature to solve related problems. A BEMS that considers electricity price and user behavior is proposed in [13]. Model Predictive Control (MPC) is used to minimize operation costs considering the system model, energy price and user behavior patterns when managing the diverse building devices. In [14], a stochastic HEMS model is presented, and the model optimizes the user cost in different Demand Response (DR) events and ensures the comfort of the inhabitants by introducing a fatigue indicator. The response fatigue is a phenomenon caused by the need to make frequent active consumption decisions, and which causes consumers to grow tired of keeping track of tariffs and usage and of having to reprogram appliances accordingly. The fatigue indicator is composed by some important factors, namely the frequency of DR signals/calls, the duration of each DR event and the extent to which appliances are affected by the DR event. Results show that by using this approach there is a reduction in the energy bill up to 42%. A stochastic approach is proposed by [15] for operating a day-ahead energy management system considering batteries, photovoltaic resources and an electric water heater. The process aims to minimize the operating costs formed by the purchase of energy from the market and the cost inherent in the aging of the battery system. The uncertainties associated with loads and photovoltaic generation are taken into account. The stochastic formulation results in a non-linear programming problem that is decomposed using the competitive swarm optimizer, which is responsible for calculating battery aging. The interaction with the market considers an aggregator that participates with active demand capacity.

A heuristic model of predictive control is proposed by [16]. A mixed integer multi-time scale stochastic optimization for load allocation is formulated. Different loads are considered such as a fan, heater, air conditioning unit, electric vehicle, dryer and washing machine. Scenarios are considered in which the HEMS serves as the control center and establishes the relationship between the consumer and the electricity retailer. Through it, consumers can participate in DR events and manage their consumption according to changes in the price of electricity. In [17], a hybrid robust and stochastic optimization model is proposed for intelligent day-ahead and real-time energy management. Uncertainties associated with PV generation and energy prices in the market are considered in the model. The robust optimization approach is used to manage uncertainties associated with the day-ahead energy price when PV generation is assumed in the worst case. Conservatism can be readjusted and energy price uncertainties are taken into account through stochastic programming. A study developed in [18] proposes a stochastic energy management system for a home with a Plug-in Electric Vehicle (PEV), batteries and PV generation. The system aims to minimize the costs associated with energy consumption in the time-of-use tariff while satisfying the demand and requirements of the PEV system. The Markov chain model of PEV mobility was used, as well as predictive models of energy demand. In [19], a rule-based system developed through data-mining techniques and application of expert knowledge is presented. The system was implemented in a building that is equipped with indoor and outdoor sensors and grid analyzers that centralize the collected information. Through the installed devices, it is possible to collect data such as temperature, humidity, lux and presence, among others. Statistical techniques and pattern study were used to create the rules.

Providing buildings with the ability to manage the energy consumption considering locally produced energy implies a suitable energy management. The main objective of this management is to control energy consumption considering factors such as current and future consumption and production, the variability of market prices and space users' comfort [20]. For this type of system to be able to make correct decisions, it is necessary that it may be adapted to different contexts [21]. The contextualization is dependent on the problem in hand and, in this sense, several authors propose different approaches that allow context identification [21–25]. In [21], the authors propose the classification of contexts for energy resources using Artificial Neural Networks (ANNs). It is found that the best classification results are achieved when considering the number of contexts that was considered optimal in the clustering phase and they conclude that an excessive number of contexts can be detrimental since similar contexts arise which ultimately deteriorate the results. In [23], the authors propose a Case-Based Reasoning (CBR) application for energy resource management. The authors conclude that the proposed system can reduce the consumption of different household applications considering the comfort of the residents. A system capable of controlling devices such as lights, air conditioning and TVs is proposed in [24] for comfort with the aim of saving energy in the building and maximizing the comfort of residents. The BEMS uses hybrid techniques to save energy based on smart context-awareness management. Various scenarios were simulated in order to test the system and the authors conclude that energy consumption was reduced by around 40%. A context-sensitive system is proposed in [25]. The model is able to manage the loads of a residence during a DR event. Time constraints, context evaluation and user comfort levels are considered. Two case studies have been carried out considering a DR event and both scenarios show positive results.

Although these works already present some initial solutions that enable the identification of different contexts, the integration of contextualization capabilities in buildings' energy management still needs significant development. Consequently, this work proposes a rule system capable of responding efficiently to problems associated with energy management under different contexts and considering the presence of multiple building users. The proposed model is experimented with using three scenarios based on real data, comprising different contexts related to different seasons of the year. Results under these scenarios are considered to analyze the decisions made by the proposed contextual rule-based system throughout the year. Three contextually distinct simulations are also considered to be run in each scenario to understand the discrepancy between the system decisions with and without considering the context.

After this introductory section, Section 2 presents the proposed methodology. Section 3 presents the case study description and includes the discussion of the results. Finally, Section 4 presents the most relevant conclusions of this work.

2. Methodology

In order to experiment with the integration of contextualization capabilities in buildings' energy management, this section presents the rule system capable of responding efficiently to problems associated with energy management under different contexts and considering the presence of multiple building users. The proposed contextual rule-based system comprises different specific components of energy management in buildings, namely Heating, Ventilating and Air Conditioning (HVAC) management, lighting control and management of generation and consumption considering energy storage systems and plug-in electric vehicles. This paper focuses on the description and analysis of the ruleset dedicated to lighting management.

Consumption Data (C) and Energy Generation (G), Current Price (CP) and Average Price (AP) of energy market, User Activity in Space (Act) and Illuminance (CB) are considered to feed the rule-based system with data.

Through the data collected by the system, it is possible to calculate Consumption State (CS), which will be the determining factor for the execution of the proposed rules. The CS variable can take on values between one and three, and the associated rules for determining it are shown in Table 1.

Table 1. Consumption State Rules.

Conditions	Consumption State
$G(i+1) \geq C(i+1)$	1
$G(i+1) < C(i+1) \wedge CP(i) \leq AP(i)$	2
$G(i+1) < C(i+1) \wedge CP(i) > AP(i)$	3

Regarding Table 1, when the forecasted energy generation G(i + 1) is equal or greater than forecasted consumption C(i + 1), the consumption state used by the system is 1.

If G(i + 1) is smaller than C(i + 1) and the current energy price CP at instant i is inferior to the average price AP, then the system considers 2 as CS.

Finally, if G(i + 1) is smaller than C(i + 1) and the current price CP is greater than the average price AP, then the system considers CS as 3.

The concept of CS is important because it defines a scope of comfort depending on the situation.

In this work, three simulations are considered. (i) Contextual (DS), which refers to the consideration of users' comfort according to different contexts; (ii) Season (S), which considers a non-fully contextualized case, but still with some preference adaptation, in this case according to the season of the year; and (iii) No Context (NC), which is completely decontextualized and assumes a single illuminance preference per user. In brief, the decontextualized rule-based system NC reflects the basis rules from the work presented in [22]. For DS, users' *Bref* is adapted with day/night and season, for S, *Bref* varies according to the season, and for NC, *Bref* is constant throughout the year. Note that the *Bref* of each user is determined according to the person's actual preference (the illuminance the user sets in the room) and it is not calculated according to pre-defined assumptions.

To understand the calculation of *Bref*, Equations (1)–(3) are presented. For the DS simulation, Equation (1) establishes the relationship between the reference brightness at time *i* for person *j* with the reference brightness for a context *k* of person *j*. In Equation (2), *Bref*(*i*,*j*) represents the reference brightness in season *l* for person *j* for simulation S. Finally, for the NC case, Equation (3) defines that the reference brightness for person *j* will be the same throughout the year.

$$B_{ref(i,j)} = B_{ref(ck,j)},\ i \in ck \tag{1}$$

$$B_{ref(i,j)} = B_{ref(sl,j)},\ i \in sl \tag{2}$$

$$B_{ref(i,j)} = const(j). \tag{3}$$

To control the lighting, a rule-based system has been devised, which, based on the provided data, is able to reach decisions regarding the regarding the increase, decrease or maintenance of illumination. The overview of the ruleset is shown in Figure 1.

First, the presence of users at time *i* is ascertained, and if there is no user in the space the lighting system stays off. If there are users present in the space, the system checks to see if there is more than one person. If there is only one person at instant *i*, the system assumes as Brightness Reference Mean $\left(B_{refM}\right)$ the preferred illumination of the person who is present at this instant and proceeds with the calculation of Brightness Comfort Interval (*BCI*) as shown in Equation (4).

$$BCI = \left[B_{refM} - B_{refM} \times (BCR \times CS),\ B_{refM}\right] \quad (4)$$

If the Current Brightness (*CB*) in the room is below the *BCI* range, the system decreases the brightness in the room, if it is above the *BCI* range the system maintains the level of illuminance and if *CB* is within the *BCI* range the system maintains the level of illuminance.

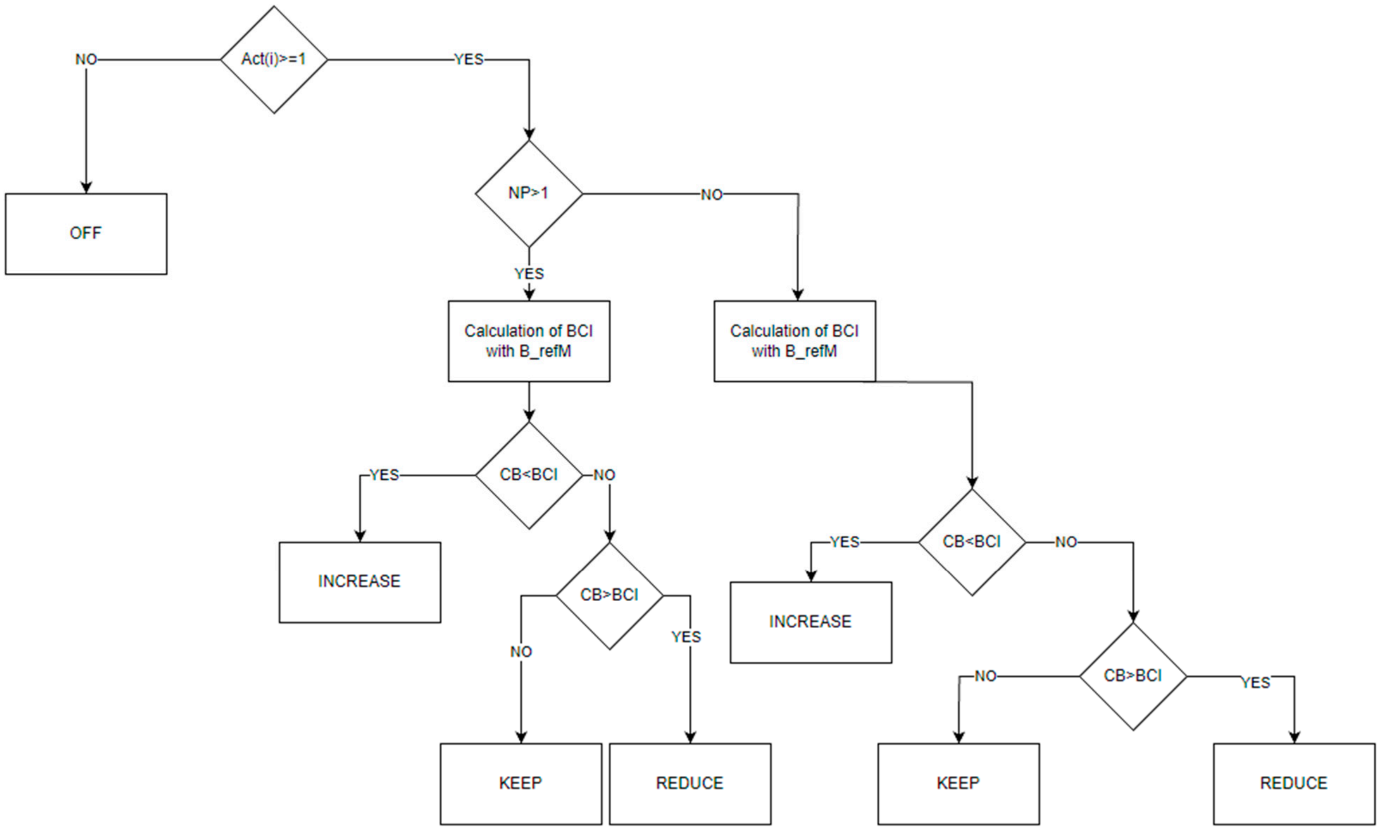

Figure 1. Rule system Flowchart.

The same is true for the case where there is more than one person in the room, however, the reference illumination becomes the average of the preferences of the people occupying the space at instant *i*.

For the calculation of B_{refM}, Equations (5)–(8) are presented.

Through Equation (5), $B_{ref}R(i,j)$ is the matrix resulting from the product of the illuminance matrix $B_{ref}(i,j)$ and the binary activity matrix *Act*(*i*,*j*). Thus, $B_{ref}R(i,j)$ contains only the reference illumination B_{ref} of those present at instant *i*.

From Equation (6), the NP vector with i entries is generated, which is given as the sum of the rows of the binary matrix *Act*(*i*,*j*) This vector is responsible for counting the number of people present in the space at time *i*.

In Equation (7), *SBref*(*i*) results from the sum of the rows of matrix *BrefR*(*i*,*j*) calculated in Equation (5). After the calculation of these auxiliary variables, it is possible to calculate the average reference illuminance for each instant through Equation (6).

Through Equation (8), *BrefM*(*i*) is given as the fraction of the vector *SBref*(*i*) and *NP*(*i*) if *NP* at instant *i* is greater than or equal to 1. Let us denote that when there is no activity at time *i*, the system considers that *BrefM* is null without inquiring whether there is activity at the next instant.

$$B_{refR}(i,j) = B_{ref}(i,j) \times Act(i,j) \quad (5)$$

$$NP(i) = \sum Act(i,j) \tag{6}$$

$$SBref(i) = \sum BrefR(i,j) \tag{7}$$

$$\begin{cases} B_{refM}(i) = \frac{SBref(i)}{NP(i)}, \; if \; NP(i) \geq 1 \\ B_{refM}(i) = 0 \qquad\qquad , \; if \; NP(i) = 0 \end{cases} \tag{8}$$

Note that *CB* values are updated to the maximum value of vectors *CB* and *Bref* whenever the system changes the brightness in the room.

3. Case Study

Three simulations are considered, with different context sensitivity, to analyze the impact of contextualization of the proposed brightness rule-based system. These were put to the test in spring and summer scenarios to evaluate the behavior of the different simulations throughout the year. In order to build the different season-dependent scenarios, datasets regarding brightness [26], PV generation and production in kWh [27], marginal price of energy throughout the day and average [28] are used. The matrices of Act representing people's activity in the space and *Bref* representing people's brightness preferences were generated to create a relevant case study.

Table 2 presents the mean absolute error of simulations S and NC compared to DS which is used as a reference. CBs of S and NC simulations were compared to CB_DS. It is possible to observe that simulation S is the closest to DS in spring and summer scenarios since it is a little contextualized. Regarding NC, it is possible to observe that CB_NC is far from CB_DS, mainly in spring.

Table 2. MAE of simulations S and NC when compared to DS—reference case, in lux.

Spring	**MAE**	**Summer**	**MAE**
S	23.97	S	25.91
NC	186.149	NC	72.17

Since MAE is an absolute error, depending on the scale of the original values one can use Figures 2–5 as a reference to enable assessing the quality of results.

3.1. Spring Scenario

Given Figure 2, it is possible to observe the response given by each of the simulations throughout the day for the spring scenario. The x-axis indicates the time and the y-axis the response of each of the simulations at a given instant. Let us denote that an increase in luminance is represented as 1 in the graphic, it is turned off at 0, a decrease in brightness is represented as -1 and for the case of maintaining the brightness it is represented as 0.5 or -0.5 depending on whether the last order given was to increase or decrease the luminosity, respectively.

Thus, considering Figure 2, it is noticeable that the NC simulation has not made any reduction in the illuminance during the whole day. This is because NC simulation is contextually disjointed from the scenario which is included. This behavior on the part of NC is worse than S and DS from the point of view of management of available resources and the user's comfort.

Regarding the response given by simulation S in Figure 2, the similarities between DS are not negligible. However, there are still some differences at 13:00 h and 15:00 h. In these periods, it is possible to observe a different behavior by DS, which, contrary to S, reduces the luminance in the room.

Figure 2. Simulations response for spring scenario.

Through Figure 3, it is possible to observe the BCI throughout the day for the spring scenario. The x-axis represents the hour and y the luminance. The blue curves represent the BCI and the pink curve the luminosity at a given instant.

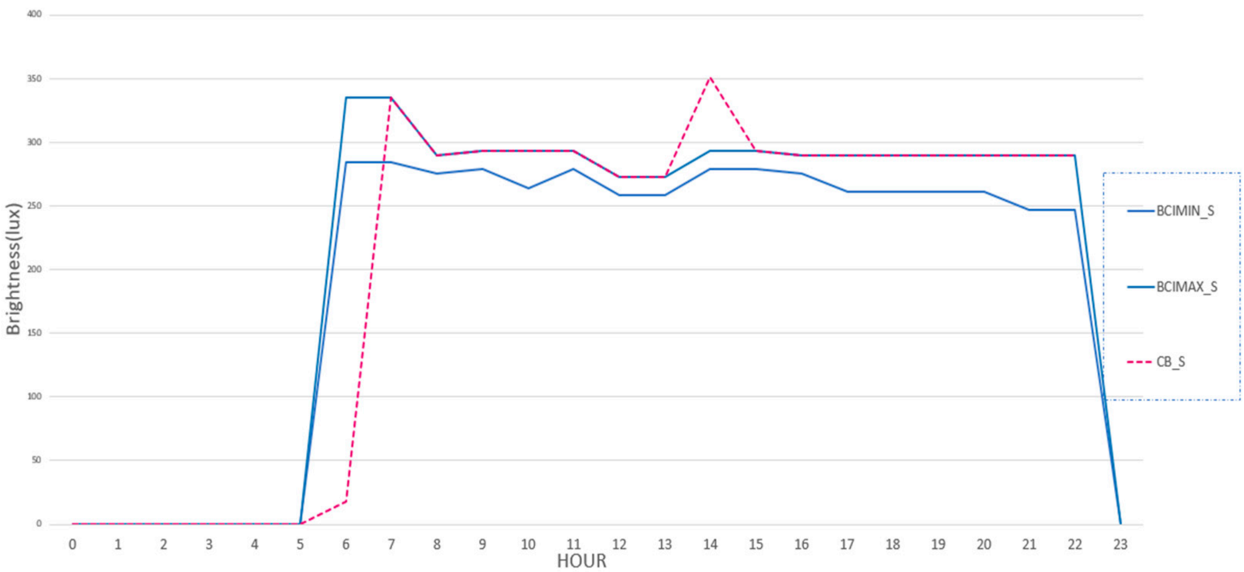

Figure 3. BCI range for S simulation during spring scenario.

Given CB_S at 13:00 h and 15:00 h, it is possible to observe that CB_S equals the value of BCI_MAX, and thus, the system considers that it is necessary to maintain the luminosity.

In contrast, Figure 4 is similar to Figure 3, however, for the DS simulation it is possible to observe that at 13:00 h and 15:00 h, the CB_DS curve is found slightly above the BCI range. Thus, DS simulation reduces the brightness at those intervals by taking advantage of a more detailed context in contrast to S.

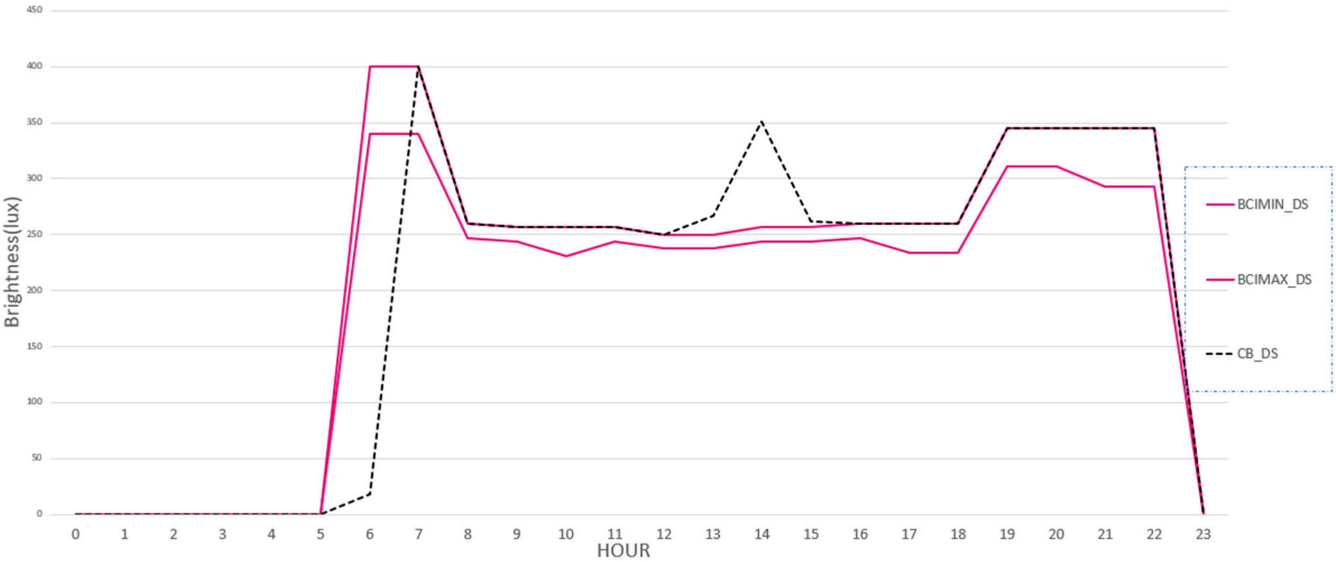

Figure 4. BCI range for DS simulation during spring scenario.

For NC simulation, the upper limit of BCI coincides with the CB_NC curve during almost the entire day which forces the system to keep a constant brightness for most of the day as shown in Figure 5.

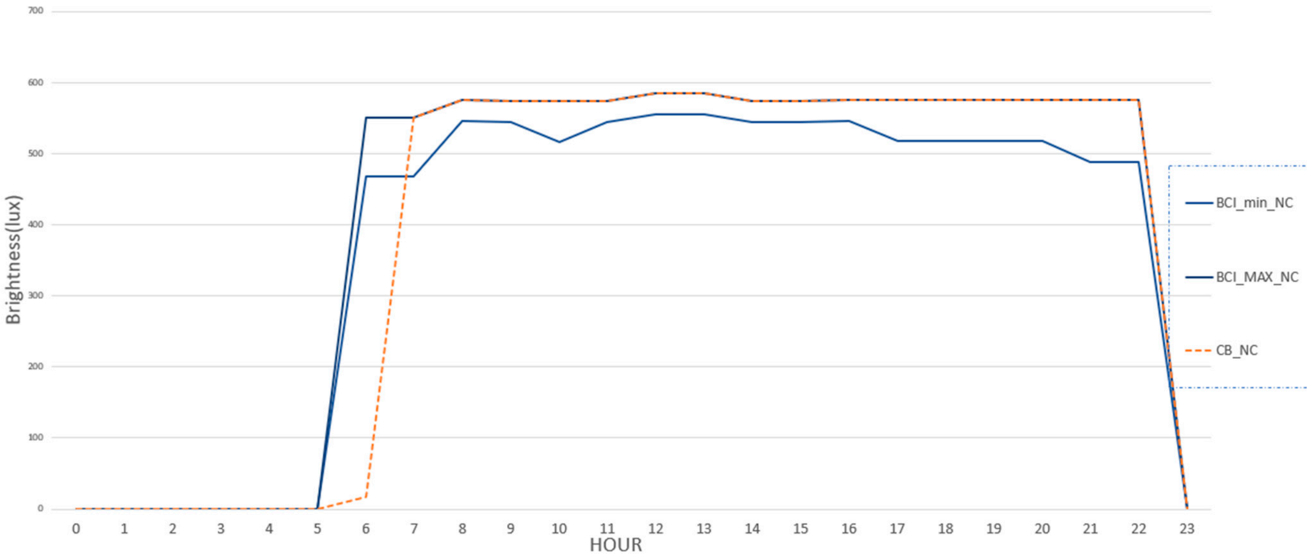

Figure 5. BCI range for NC simulation during spring scenario.

In summary, DS can take advantage of periods with excessive brightness to practice better management of available energy resources without neglecting the user's preferences.

Figure 6 establishes the relationship between the behavior of different simulations and the price of energy at a given instant. High price is represented with 1 and low price with 0 in the graph. Again, the increase in brightness is represented with 1, a decrease with -1, off with 1 and 0.5 or -0.5 for keeping the brightness dependent on whether the last action given was increase or decrease.

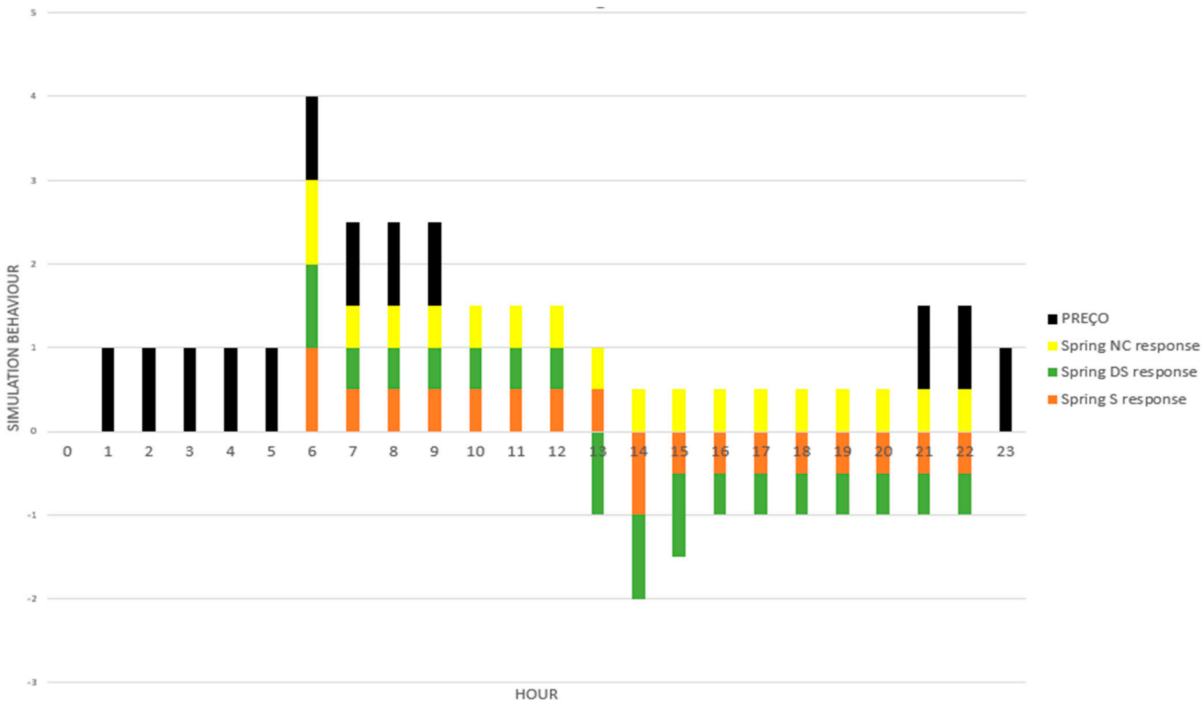

Figure 6. Energy price vs. simulation response for spring scenario.

Simulations of DS and S are able to reduce the illuminance without compromising the user's preferences in periods when the price of energy is considered high, however, the same is not true with NC. This, it is noticeable that contextualized simulations like DS and S show a better response.

3.2. Summer Scenario

Regarding the summer scenario, Figure 7 establishes the relationship between the behavior of different simulations and the price of energy at a given instant. Once again, we can see a similar response between DS and S simulations and NC being far from that.

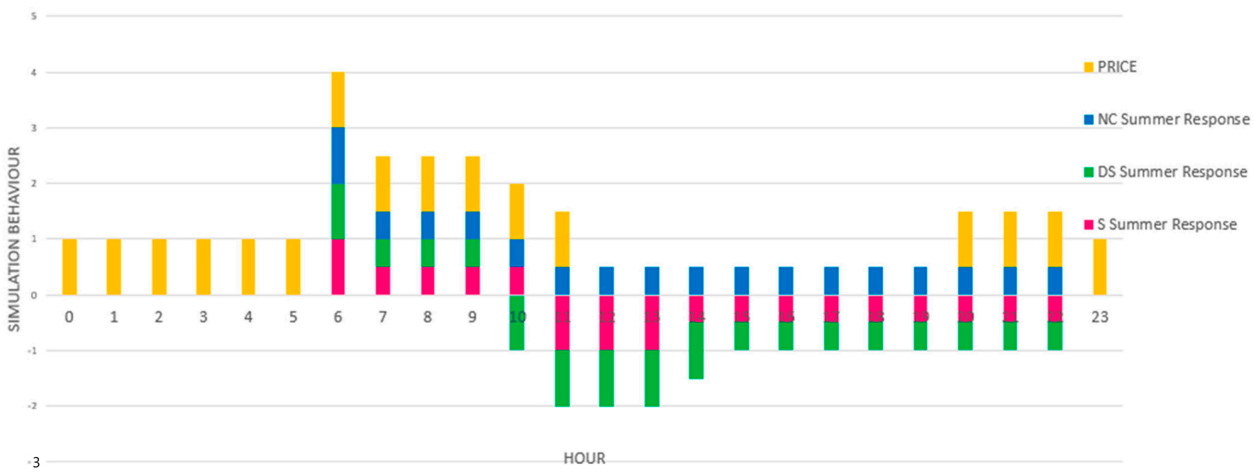

Figure 7. Energy price vs. simulation response for summer scenario.

Simulation of DS has the highest number of luminosity reductions followed by S that, although not able to reduce the lighting level at 10:00 h and 14:00 h like DS, shows a pleasant response throughout the analyzed day. Through Figure 7 it is possible to verify that NC presents a response without any reduction throughout the day due to the lack of contextualization inherent in NC.

Based on Figure 8, it is possible to observe the behavior of BCI_DS for the summer scenario. It is noticeable that the value between 10:00 h and 14:00 h CB was above the BCI range. Consequently, DS can reduce the excessive brightness in those instances. Thus, DS can save energy resources and ensure the comfort of the users.

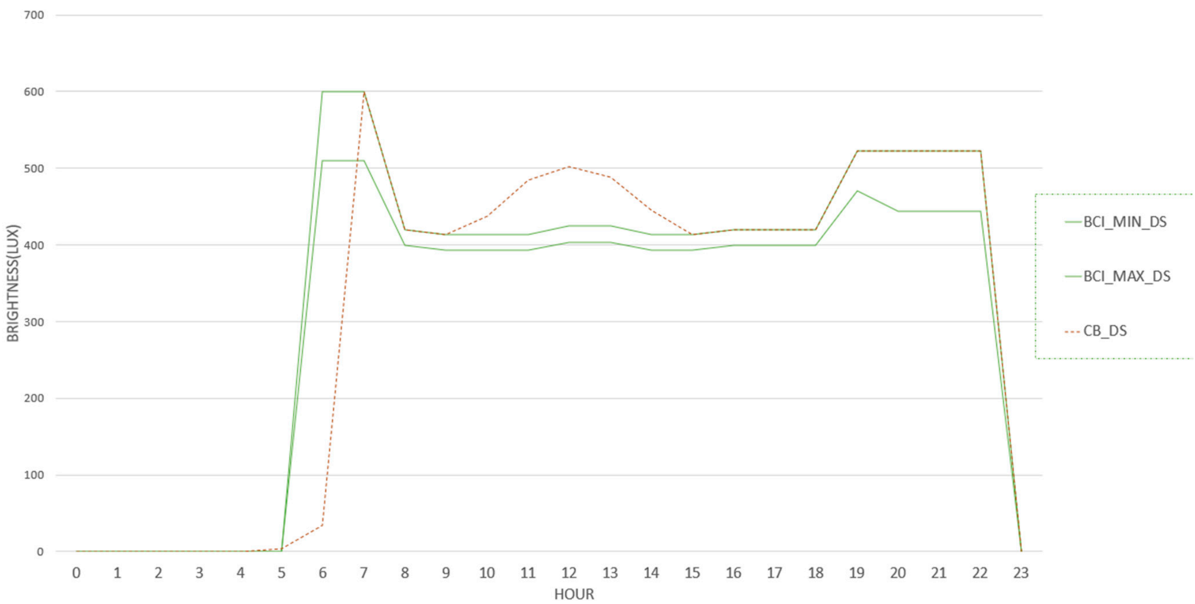

Figure 8. BCI range for DS simulation during summer scenario.

The behavior of BCI_S can be observed in Figure 9, where simulation S once again is very similar to DS in terms of BCI range. Thus, the DS and S responses are close.

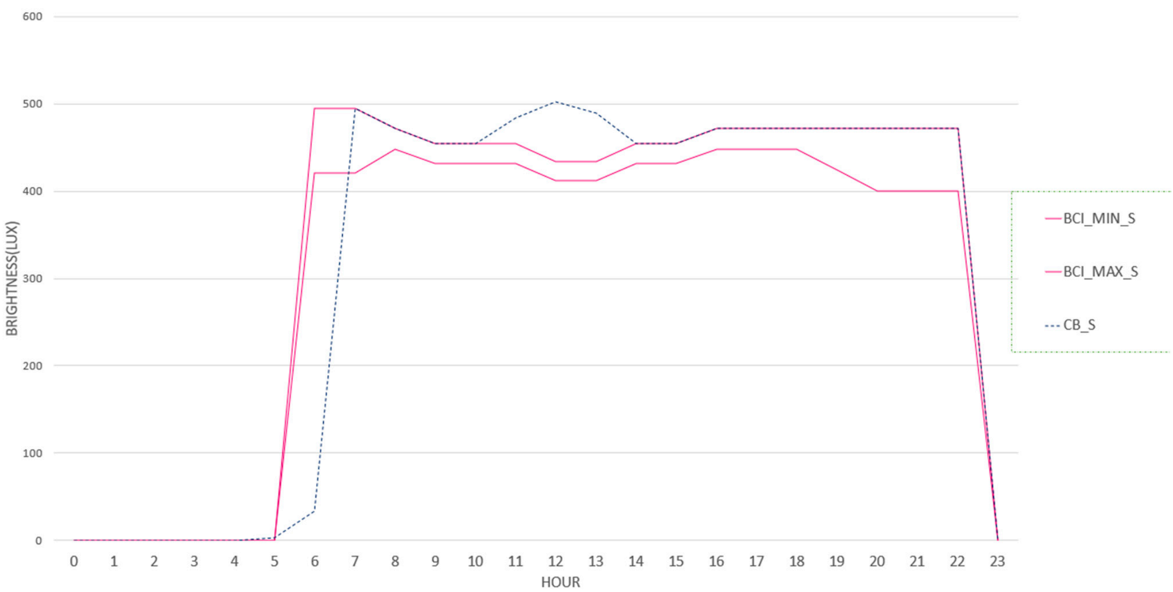

Figure 9. BCI range for S simulation during summer scenario.

For simulation S, the reductions in the room brightness occurs less frequently since simulation of S does not have the necessary customization like DS. Consequently, it uses the same preferences throughout the day and is not capable of distinguishing day/night and uses higher values of brightness all day. Thus, it is not capable of taking advantage of the spike of brightness from 10:00–14:00 h.

Regarding NC, Figure 10 shows once again the inability of this simulation to adapt itself to the situation that is inserted into and, consequently, the way the system manages the energy resources and the user's comfort is not optimal.

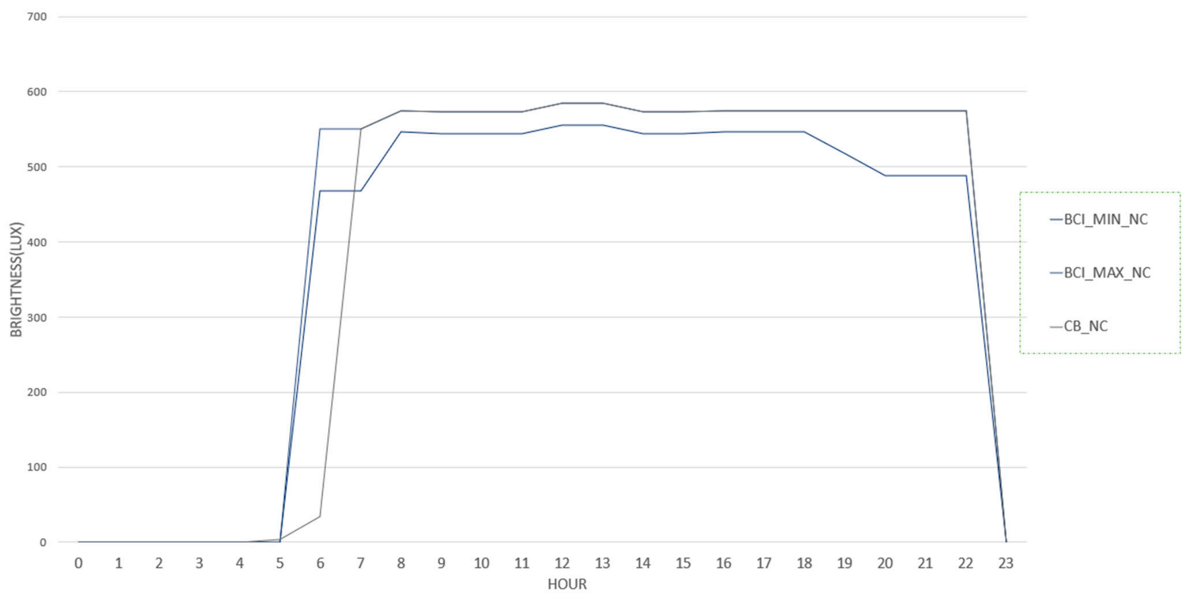

Figure 10. BCI range for NC simulation during summer scenario.

3.3. Energy Costs

In order to assess the impact of using the proposed model in terms of energy costs, an analysis of energy sales and purchases is conducted. This analysis considers the integration of the brightness rule-based system in a comprehensive energy management system that includes the management of other consumption devices, the sale and purchase of energy, and the storage in residential batteries. Figure 11 shows the periods of the day in which energy purchases are conducted for a scenario with full contextualization (PC) and with season only as contextual information (PS), considering a winter scenario.

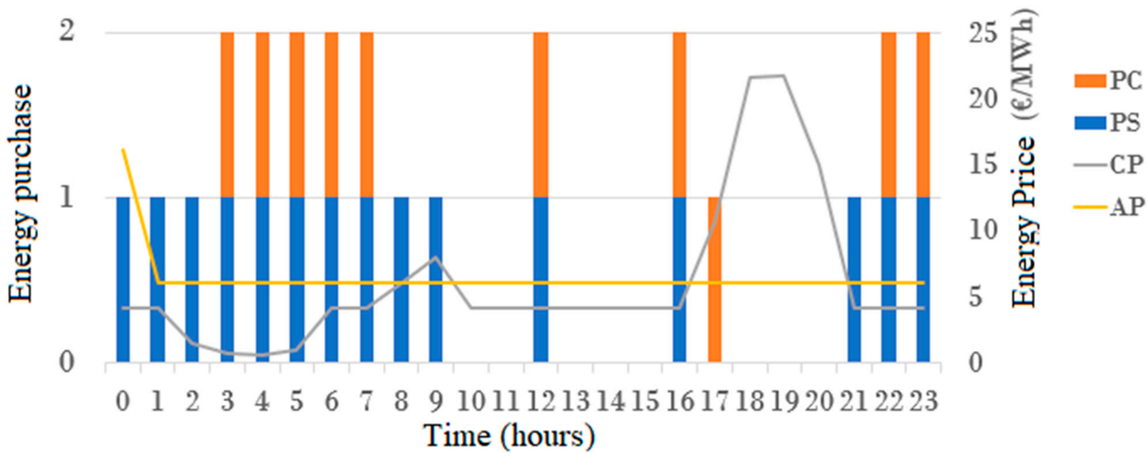

Figure 11. Energy purchases considering contextualized and semi-contextualized rule-based system for the winter scenario.

From Figure 11, it is visible that the contextualized model PC results in a reduced number of periods in which an energy purchase is made when compared to PS. Moreover, it can be seen that most of these purchases are made in periods in which the Current Price (CP) is lower than the Average Price (AP). If fact, the only period of the day in which this does not occur is in hour 17. Figure 12 shows the comparison of the periods of the day in which energy sales and purchases are conducted for PC and PS considering a summer scenario—with a higher amount of PV generation—thus resulting in several periods with surplus energy to be sold.

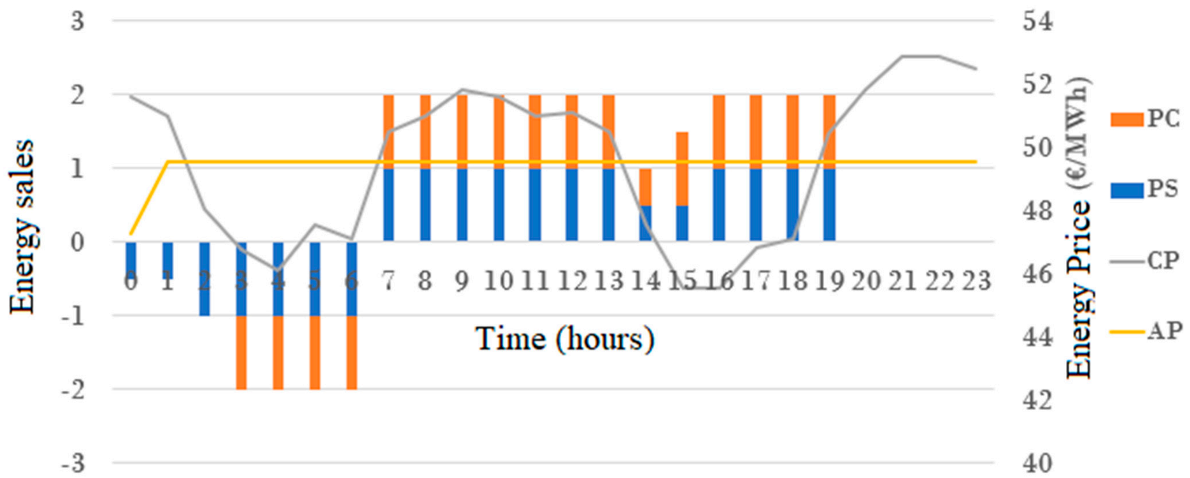

Figure 12. Energy sales considering contextualized and semi-contextualized rule-based system for the summer scenario.

From Figure 12, one can see that the periods in which sales occur (positive values) are similar when comparing the results of PC and PS. However, PC leads to a smaller number of periods in which purchases are required. This means that, overall, using PC leads to lower energy costs, as can be seen by Table 3.

Table 3. Cost balance, in EUR for the considered winter and summer days.

Profit (EUR)	PS	PC
Summer	0.48	0.62
Winter	−0.10	−0.08

From Table 3, it can be seen that the profit with energy purchase when considering PC is higher than when considering PS, for the summer scenario. On the other hand, in the winter scenario, since there is no surplus energy to be sold, the profit assumes negative values with both PC and PS. These costs are, even so, lower when using a contextualized approach with PC.

4. Conclusions

The evolution of building energy management systems can benefit significantly from the contextualization of the decisions, especially when considering spaces that involve multiple users. This paper proposes a novel contextual rule-based system to support energy management in buildings, considering the contextualization of the decisions and taking into account the possible presence of multiple users at different times. The proposed model uses the prediction of users' presence, of local generation, of electricity prices and of user preferences to reach contextualized decisions.

Results using a case study based on real data show that, by analyzing the specific management of lights against users' brightness preferences, contextualized decisions are able to guarantee the multiple users' comfort in a better way than non-contextualized or semi-contextualized models, while maintaining low energy costs. The impact has been analyzed regarding the actions that are performed (increasing, maintaining or reducing the brightness of a room) according to the needs and preferences of the set of users that is present in the room in each moment. The impact of considering contextualized decision making is also assessed in terms of costs/profits resulting from the energy sale and purchase under different scenarios. From the achieved results, it can be seen that applying contextualized decisions leads to lower energy costs and higher profits with the sale of energy surplus, while maintaining the room luminosity within the preferences of the set of users.

As future work, the development of similar contextual rulesets for other resources such as HVAC is suggested. Additionally, consumer behavior modeling could be incorporated in the proposed model as means to capture and automatically adapt the users' preferences that are considered by the model.

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