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Design and validation of a predictive energy management strategy for self-consumption in tertiary buildings

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***Abstract*—This work presents a predictive energy management strategy for self-consumption in tertiary buildings. The self-consumption is composed of a photovoltaic generation and a battery. The energy management strategy is composed of a forecast module, high-level strategy and real-time adaptative control. Due to the daily forecast, significant data was available 24 hours in advance, allowing the energy management strategy to take advantage. The high-level strategy defines the battery's operation mode for each hour of the day. The real-time adaptative control corrects the possible errors with instant measurements and generates real-time battery commands and its operation mode. With this approach, a reduction of 16.17 % of the electric bill was obtained by comparing it to a scenario without a battery and its correspondent strategy. The development was integrated and validated in a test bench, obtaining a 60.43 % grid independence increase.**

***Keywords*—Self-consumption, tertiary building, school, energy storage system, adaptative control, regression tree.**

I. Introduction

The amount of electricity consumed by the commercial and public services sector in 2019 was about 29 % at the European level generating 4.6 % of the CO_2 [1]. To combat these issues, in 2018, the European Renewable Energy Directive (RED II) fixed for 2030 a 32 % renewable energies target to achieve climate neutrality in 2050 [2]. Spain started new strategic frameworks; [3] and [4], fixing the objective to install more than 122 GW of renewable generation, where 32 % will be solar photovoltaic. In this part, the photovoltaic self-consumption must play an essential role; it must address at least 9 GW of installed power. In this framework, law 7/2021 [5] raises energy and climate objectives for 2030 and 2050 to the legal level to boost the population taking part in it. Moreover, Royal Decree 477/2021 [6] gives subsidies, in concrete, to self-consumption and energy storage, oriented to the economic sector as well as to the residential, public, and tertiary sectors.

A self-consumption installation is made up of one or more renewable generation installations and by the consumer member, in which both generation and consumption must be close [4]. Introducing self-consumption benefits by reducing a) electricity demand, b) grid consumption, c) electricity bill, and d) power losses in the transmission and distribution lines [7]. This offers consumers more control and awareness over their consumption and reduces the effect of the variability of fossil fuel prices [4]. However, renewable energies concern people because they are intermittent resources. Predictions are used to cope with this problem, particularly statistical and artificial intelligent approaches like linear regression models, fuzzy systems, and artificial neural networks, among others [8]. Apart from that, consumption and electricity price predictions must be considered to create a correct energy management system. In these fields, regression trees are commonly used machine learning techniques due to their simplicity and accuracy [8], [9].

As previously mentioned, self-consumption is a crucial element in reaching climate neutrality. Consequently, this paper presents the design, development and validation of a predictive energy management strategy (EMS) for self-consumption in tertiary buildings, scoped as a school in this research. The school's self-consumption is composed of photovoltaic generation, solar panels on the roof and an energy storage system that is integrated via a converter. The scenario that had been validated was composed of a lithium-ion battery module and three converters connected to the grid of 8 kW each, changing from constant current to triphasic alternating current. The developed EMS consists of three blocks; the first one generates daily forecasts (solar irradiance, power consumption and electricity price) using regression tree algorithms. Then, the second one generates high-level operation commands based on the previous predicted data. The last one provides the final operation commands by a real-time adaptative control module. Finally, the main results obtained in the simulations and in the experimental validation are presented in this work, also making an economic balance.

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This paper is structured as follows: Section II describes the case study of the present work, continued by the parameter modelling in Section III. Afterwards, in Section IV the proposed design of the predictive energy management strategy is explained. Consequently, in Section V, the used test bench for the battery integration, and in Section VI, the obtained results and the related discussion are shown. The paper finishes summarising the main conclusions in Section VII.

II. CASE STUDY

The work is based on a school's predictive EMS for self-consumption. The school is located in Usurbil (Spain) and has a photovoltaic generation installation. Due to that, the aim of the school is to increase the self-consumption of specific loads by integrating an energy storage system (ESS), concretely a battery. The named loads are heating, ventilation and air cooling (HVAC). As it is a specific part of the consumption of the school, the HVAC consumption value could be treated as a domestic consumption value. That is why it is assumed that the school has contracted a 2.0TD tariff (Spanish domestic electricity tariff in 2022, BOE-A-2021-21208) with a contracted power of 10 kW [10].

The configuration of the whole installation is shown in Fig. 1. The photovoltaic installation (PV installation) is composed of 32 panels, being 10 kW in total installed power. The battery integrated (ESS system) has lithium-ion chemistry, with 360 Ah, 48 V and 17.2 kWh characteristics. There will be used three converters to change direct current to alternating current, each one of 8 kW.

III. MODELLING

This section presents the used equations for modelling the parameters of PV generation, consumption and battery State of Charge (SOC). These equations were integrated into MATLAB to generate generation, consumption and battery SOC values.

A. *PV generation*

The power generated by a solar photovoltaic panel (P_{PV} in [W]) is calculated by the expression that involves the installed power (P_{inst} in [W]), the instantaneous irradiance (G_{inc} in [W/m^2]), the panel temperature and power coefficient (δ in [%/ºC]) and the cell temperature (T_{cell} [ºC]), as it is shown in (1).

$$P_{\text{PV}} = P_{inst}\left(\frac{G_{\text{inc}}}{1000}\,(1+\delta\,(T_{\text{cell}}-25))\right) \tag{1}$$

The irradiance data is obtained from the database available in Euskalmet of the meteorological station of Lasarte [11], the nearest location to Usurbil. Considering that there is no database available of the temperature of the cells, this one was calculated with the following expression (2)

$$T_{\text{cell}} = T_{\text{amb}} + G_{\text{inc}}\left(\frac{NOCT-20}{800}\right) \tag{2}$$

where the ambient temperature (T_{amb} in [ºC]) is also taken from the same database as the irradiance, and the Normal Operating Cell Temperature is panel technical data (NOCT in [ºC]).

B. *Consumption*

Consumption profiles were obtained from the database of IKERLAN, where there was available a consumption profile of a school of Gipuzkoa, previously employed in [12]. This profile was scaled in this work because only specific loads were considered for the self-consumption schema, as it was mentioned in the case study.

C. *Battery SOC*

The battery SOC is calculated by the Coulomb Counting algorithm, which is employed to emulate the battery. The *SOC* in [%] is calculated between the initial SOC and the percentage of the capacity charged or discharged respect the nominal capacity, as is shown in (3). This is calculated by integrating the current across the battery (I_{bat} in [A]) over the time (from t_0 to t) respect the rated capacity (Q_{rated} in [Ah]) [13]. Converter efficiency is neglected in this work.

$$SOC(t) = SOC(t_0) + \frac{\int_{t_0}^{t} I_{\text{bat}}\,dt}{Q_{\text{rated}}}\,100 \tag{3}$$

IV. ENERGY MANAGEMENT STRATEGY DESIGN

EMSs are essential to avoid energy wastage in self-consumption installations. To have a higher self-consumption percentage, meaning a reduction in the electric bill, ESSs are integrated. Besides, adding an ESS increases the complexity and difficulty of EMS.

In this section, the designed EMS is explained, which was composed of three blocks, as shown in Fig. 2. The first one generated daily forecasts (solar radiation, power consumption and electricity price) based on regression trees algorithms. The output will be a daily forecast with a one-hour time step. Then, the second one, called high-level operation, generated commands based on the previous predicted data at the same time step. The last one provided the final operation commands by a real-time adaptative control module.

A. *Forecasts*

The forecast module was used to obtain a more efficient and accurate EMS. As mentioned before, integrating a battery into the self-consumption installation adds complexity. In this way, forecasting the key factors (solar generation, load consumption and electricity price) allowed the EMS to anticipate the tendencies of the day.

The selected forecasting technique, based on historical data, was the regression tree, which is a machine learning method.

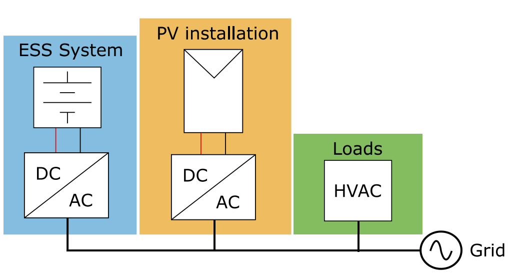

Fig. 1: Installation main configuration

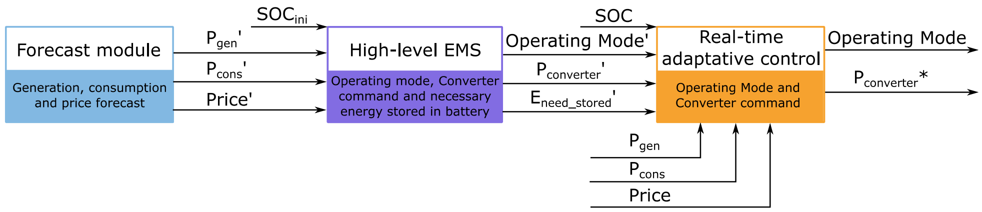

Fig. 2: Energy Management Strategy main diagram

As aforementioned, thanks to their simplicity and accuracy, regression trees are widely used for trend analysis [8], [9]. Regression Trees are decision trees with the particularity that they predict continuous outputs instead of discrete outputs. There are different decision tree models, a) fine tree, b) medium tree, c) coarse tree, d) optimisable tree and e) ensemble models. This last one combines various decision trees resulting in a technique with a better forecasting performance [8]. Here two types exist, the boosting and the bagging models.[8]

In this work, the selection and the design of the Regression Trees were made through the Regression Learner App of MATLAB [14]. This tool enables to train and validate the mentioned models quickly for later to be compared with their validation errors. Once selected, the best regression model was exported to the workspace.

1) Solar irradiance: The dependency of photovoltaic generation on weather becomes an intermittent energy resource. The solar irradiance is proportional to the power generation, as seen in (1); thus, solar irradiance was predicted. All mentioned models were trained in the Regression Learner App with historical data (from 2019 and 2020 years). The input parameters of the model were the temperature, humidity, wind speed, precipitation, irradiance, previous day irradiance, hour, day, month and year. The best performance was obtained with the bagging module, and consequently, this model was the selected one.

2) School consumption: The same process was proceeded to predict school consumption, but in this case, the historical data and the module's inputs changed. The historical data was from 2017, and the input necessaries for the model are the temperature, consumption, minute, hour, day, month, weekday, weekend and if it is a holiday. In this case, the fine tree performed best. Consequently, the selected module was the fine tree.

3) Electricity price: In this case, the historical data for 2021 was obtained from the database of OMIE, the Iberian Peninsula electricity market operator [15]. The input data was composed of the price, previous day price, hour, day, month and year. Likewise, in solar irradiance, the bagging tree obtained the best performance, resulting again in the best option.

B. High-level operation commands generator

Once the forecast of the day was done, the high-level operation command generator generated three arrays, a) inverter power command, b) operating mode, and c) the necessary energy stored in the battery for each hour of the predicted day. These commands were the result of a rule-based strategy whose inputs were the predicted data and the initial SOC of the battery. The necessary energy stored (E_{n} in Wh) was calculated by adding the energy difference between the generation (E_{gen} in Wh) and consumption (E_{cons} in Wh), when the generation was lower than the consumption and the electricity price ($PVPC$ in €) was higher than the average ($PVPC_{\mathrm{mean}}$ in €), as shown in (4).

$$E_{\mathrm{n}}(t) = E_{\mathrm{cons}}(t) - E_{\mathrm{gen}}(t) \tag{4}$$

$$\left(if\ E_{\mathrm{gen}} < E_{\mathrm{cons}}\ \&\ PVPC(t) > PVPC_{\mathrm{mean}}\right)$$

The aim of the strategy was to reduce the electricity bill by taking advantage of the battery and the predictions. As the trends of the day were known, the strategy ensured that the battery would be charged with the necessary energy to avoid consuming electricity from the grid when the prices were high.

To achieve the mentioned objective, six operating modes were defined, as represented the Fig. 3, 1) stand-by mode, 2) charging the battery and 3) discharging the battery, and 4), 5) and 6) are the same as the previous three but assuring that the battery must store the necessary energy. The if-then rules to define the operating mode depended principally on the difference between generation and consumption, the battery SOC level, and the electricity price level. Also, it must be mentioned that in this work, it had been contemplated the ability to charge the battery from the generation, from the grid or both in the charging modes (2 and 5). Likewise, in the discharge modes (3 and 6), the battery can be discharged to the consumption, the grid or both.

The peculiarity of the operation modes with the necessity of energy stored in the battery (4, 5 and 6) was that, as the strategy had identified the high electricity price time period, the battery is charged from the solar generation and/or from the grid in periods of low electricity price. For example, being the E_{BT} the available energy in the battery in (Wh), in the case that the battery is charged ($E_{\mathrm{BT}} > E_{\mathrm{n}}$), the energy generation is analysed. If the generation is not sufficient to supply the consumption and, in the next three hours, is going to need E_{n}, the battery will be discharged until the aforementioned E_{n} limit.

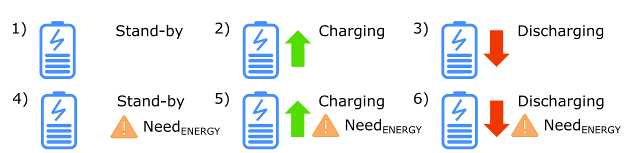

Fig. 3: Operation modes of the EMS

In the strategy, some limits were defined to make sure that the battery was operating at the levels that the fabricant recommended. In this way, the degradation of the battery will be lower, and the battery life will be longer. Therefore, battery charging and discharging powers (P_{cha} and P_{dcha}, both in W) are limited to $P_{\mathrm{cha,max}}$ and $P_{\mathrm{dcha,max}}$ due to the current limits, as in (5) and (6), and the maximum and minimum SOC, as in (7).

$$P_{\mathrm{cha}}(t) \leq P_{\mathrm{cha,max}} \tag{5}$$

$$P_{\mathrm{dcha}}(t) \leq P_{\mathrm{dcha,max}} \tag{6}$$

$$SOC_{\mathrm{min}}(t) \leq SOC\ (t) \leq SOC_{\mathrm{max}} \tag{7}$$

Grid power limits were also integrated, being, in this study, the contracted power (P_{contr} in W), summarized in (8) and (9).

$$|P_{\mathrm{cons}}\ (t)| \leq |P_{\mathrm{contr}}| \tag{8}$$

$$|P_{\mathrm{PV}}\ (t)| \leq |P_{\mathrm{contr}}| \tag{9}$$

C. Real-Time adaptative control

Finally, the role of the Real-Time adaptative control was to correct the operation mode and the converter command in case the predictions had an error. This was made with real-time measurements of the power generation, power consumption, electricity price, battery SOC and predicted converter command, operation mode and needed energy stored in the battery.

The control was based on correcting the operation mode and checking that real-time conditions were the specified ones in each operation mode. For each case another rule-based strategy, based on the previously mentioned strategy (not setting the needed energy stored aside) was integrated. Consequently, the outputs of the real-time control module were the real converter command and the operation mode, being the result of the instantaneous measurements.

V. Scaled Test Bench

The experimental validation of the previous scenario was carried out with a scaled test bench, see Fig. 4. The hardware consisted of: a) an LFP chemistry battery of 48 V, 180 Ah and 8.64 kWh characteristics, b) three DC/AC converters, each of 8 kW and, c) the necessary communication devices for the control. The software in the computer embraced a) the communications for the control of the devices and b) the main program, where both were developed in LabVIEW.

The main program allows the fast validation of the EMS. It simulates one day in 144 seconds. Meanwhile, the control of the converters and the battery monitorization is done in real-time (with an execution rate of one second).

VI. Results and Discussion

The proposed scenario and EMS were simulated and validated in MATLAB and also validated experimentally on the test bench. Two different scenarios were simulated: the first one of a one-day operation to validate the correct energy flow and the second one, the 2021 whole-year simulation to obtain economic results.

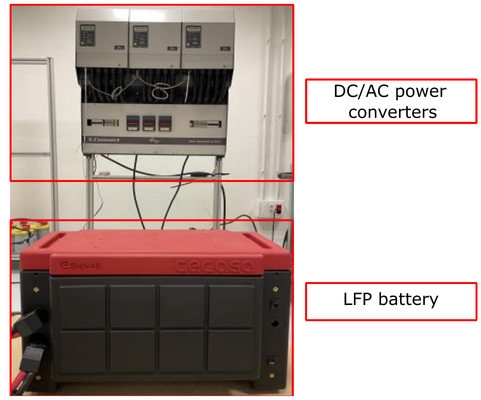

Fig. 4: Battery integration for self-consumption test bench

For the energy flow simulation, the 23rd of March 2022 data was employed. The generation profile introduced was collected and scaled from the real database available in IKERLAN. The consumption, as previously mentioned, was from a previous study [12]. Lastly, the SOC of the battery was calculated in the way explained in Section III.C.

Fig. 5 depicts the power flow, where the blue line is the solar power generation, the red line is the power consumption, the yellow one is the converter power flow which is the battery power flow and the purple line is the amount of power consumed from the grid. Furthermore, Fig. 6 presents the SOC and electricity prices during the simulated scenario, being the

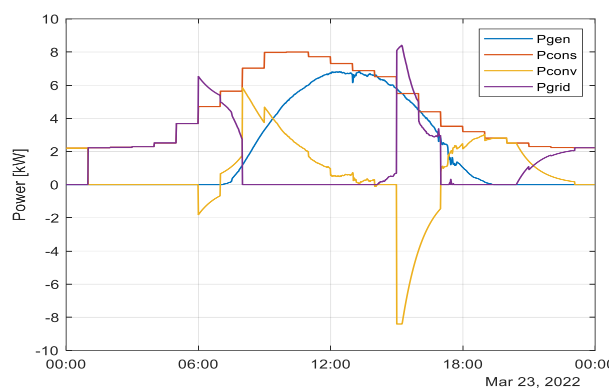

Fig. 5: Power flow of the scenario on 23/03/2022

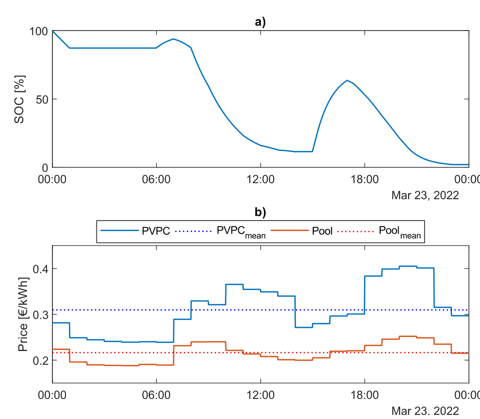

Fig. 6: The a) battery SOC and b) electricity price of 23/03/2022

a) graph the battery SOC and in graph b) the blue lines are the PVPC and PVPC average and the red ones the pool and pool average prices. As it is shown, until the electricity price is decreased to a low value ($0.9\,PVPC_{\mathrm{mean}}$) the battery is discharging to the consumption. After that, the battery operation changes to stand-by and the grid feeds the consumption due to the low price. At 6 a.m., it can be seen how the battery was charged because of the E_{n} due to the high prices that come after. Whereas the generation is increasing, it can be seen how the battery demand is getting lower. Meanwhile, as it is coming again the high price period, the battery is charged from the grid with low prices. Finally, the battery supplies the consumption until it is discharged. Throughout the simulation could be validated that the grid did not surpass the contracted power and the battery never exceeded its maximum power, respecting the power limits ($P_{\mathrm{cha,max}}$ and $P_{\mathrm{dcha,max}}$).

To evaluate the economic side, the presented approach was simulated and the electricity bill was calculated where the energy surpluses were paid with the pool price. This electricity bill was compared to a scenario without a battery nor its correspondent EMS. The reduction of the electric bill was obtained with the presented approach with respect to the actual self-consumption installation (just PV installation). Fig. 7 shows the 2021 electric bills for both self-consumption installation (Self-consumption PV) and the self-consumption installation with the battery and the EMS (Self-consumption PV, battery as BT and EMS).

Comparing the annual, it was seen that the average percentage reduced due to the battery and the EMS was around 11 %, calculated employing (10). This means a direct reduction of 864.7 € of the total 2021 electric bill. It was remarkable that the higher reduction obtained was in July with 16.17 %. In summer, weather conditions are better, meaning a higher solar production, and due to summer break in Spain (schools are closed), the consumption was the stand-by power.

$$Annual_{REDUCT} = \frac{\sum(Bill_{\mathrm{EMS}} - Bill_{\mathrm{PV}})}{\sum Bill_{\mathrm{PV}}}\,100\% \quad (10)$$

Where $Annual_{REDUCT}$ is in (%), the $Bill_{\mathrm{EMS}}$ is the electric bill of the scenario with self-consumption with the battery and the EMS (in €) and the $Bill_{\mathrm{PV}}$ is the electric bill of the scenario with self-consumption with only photovoltaic generation (in €).

Moreover, the experimental validation was carried out in the test bench presented in Section V. Four different days were validated, obtaining a correct operation of the designed predictive EMS. All the power limits were correctly respected and the power flow and operation modes were well defined. Apart from that, in the validation of 19/03/2022 (weekend, having idle power consumption), the level of independence from the grid of the self-consumption installation with PV generation was 38.54 %. Comparing that same scenario with battery and EMS integration, 61.83 % was obtained, resulting in an increase of 60.43 %.

Both simulation results and experimental validation prove that the integrated EMS algorithm reduces the electric bill and ensures that the energy flows correctly in each operating mode, decreasing grid energy consumption in expensive periods. Finally, the amortisation of the battery integration installation

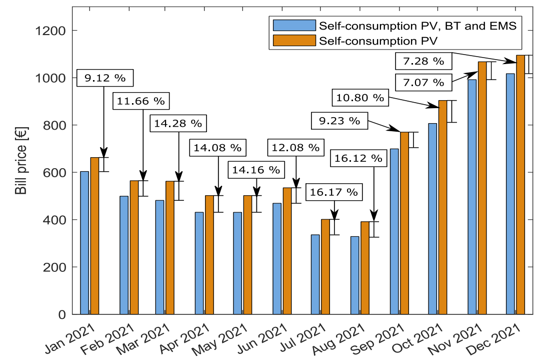

Fig. 7: Electric bills of 2021

was ten and a half years, calculating a minimum battery life of eleven and a half years. Thereby resulting in interest the battery integration with a predictive EMS into the previously set self-consumption installation, obtaining at least one year of direct savings.

VII. CONCLUSIONS AND FUTURE LINES

In this work, a predictive EMS for self-consumption in tertiary buildings, a concrete case of a school, was presented. This scenario was validated in the scenario mentioned in the case study. For the validation via simulation, two different simulations were made, the first one on the 23rd of March 2021 and the second one on the whole 2021 year.

The results obtained showed that, firstly, all the operation modes were defined and operated correctly, respecting all the grid and battery constraints. It was concluded that the real-time control module in the EMS was essential due to the forecast errors.

Due to the forecast stage, the day generation, consumption and price tendencies were obtained. Forecasts together with EMS resulted in the reduction of the electric bills, concluding that all the parts of the EMS are necessary. In terms of economic results, up to a 16.17 % decrease in the electric bill was obtained, demonstrating the importance and necessity of a correct EMS. The lowest electric bill was obtained in summer because it is the season with the highest irradiance in this location, the northern hemisphere.

It must be mentioned that the integration of the EMS in the test bench with the battery was successfully carried out, obtaining higher independence from the grid. Concluding that could be integrated into a self-consumption installation for residential buildings.

It is to mention that in this study, the battery degradation model was neglected, so, with time, the battery operation range will be decreased, and this error will be corrected. In ongoing research, additional SOC limitations are going to be studied. Restricting the operation range of the battery to maintain a SOC_{average} will prolong battery life. However, the impact of integrating this limitation must be reviewed and evaluated. Finally, a collective self-consumption scenario will be considered for the next studies.

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