Dispatching policies for stationary battery storage in the presence of photovoltaic systems and electric vehicle supply equipment

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Abstract: Energy systems are experiencing a growth of distributed generation from Renewable Energy Sources (RES) thanks to their contribution to the transition towards sustainable systems. The adoption of Battery Energy Storage Systems (BEESs) represents a key-enabling technology to increase the penetration of RESs, as they can mitigate their main drawbacks (i.e., intermittency and uncertainty) by enabling the capability of non-simultaneous production and consumption. BESSs are typically operated by implementing rule-based algorithms, mainly aiming at increasing the self-consumption of the energy produced by renewables. Nevertheless, different dispatching policies can be applied, particularly in the presence of intermittent but relevant load demands, such as those introduced by electric vehicle supply equipment. In this study, the System Advisor Model developed by the National Renewable Energy Laboratory of the United States of America was used to test and compare different BESS dispatching policies by referring to a real case study. The reference use case is a building located in the engineering campus of the University of Brescia, Italy, equipped with a 64 kWp photovoltaic system and a 25.2 kWh and 13.8 kWp Lithium-Ion BESS. The results of the analyses show that the semi-automatic Automated Grid Power Target policy was the most performant for the considered use case, both in terms of demand peaks reduction and load shifting, by, at the same time, providing relevant flexibility options. These results can be used as managerial insights supporting policy makers and energy system users for the evaluation of dispatching policies.

Keywords: dispatching policies; energy storage systems; batteries; electric vehicles.

I. INTRODUCTION

Global warming is one of the main issues that our society must face and resolve in the upcoming years. Polar ice shields are melting, and the sea is rising. In some regions, extreme weather events and rainfall are becoming more common while others are experiencing extreme heat waves and drought. These impacts are expected to intensify in the coming decades. Moreover, developing countries are mostly affected. People living there often heavily depend on their natural environment and have the least resources to cope with the changing climate [1]. The main causes of this phenomenon are huge CO_2 and other greenhouse gases emissions. To reduce the impact on the environment, modern societies are focused on the development of green systems, by promoting the large use of distributed generation from Renewable Energy Sources (RESs) [2]. At the same time, the adoption of distributed Battery Energy Storage Systems (BESSs) has been also promoted to mitigate the drawbacks caused by the intermittent generation of RESs such as Photovoltaic (PV) systems [3]-[6]. The use of BESSs has also been investigated to ensure the efficient and secure operation of distribution grids by providing multiple services, such as energy arbitrage, ancillary services, and active/reactive power control [7]-[9]. The decarbonization process has more recently also interested the vehicular mobility, which is rapidly transitioning from internal combustion engines towards Electric Vehicles. Battery EVs (BEVs), i.e., EVs equipped with onboard BESSs, are generally considered one of the most promising solutions, as they are independent from the energy source used to supply the onboard electric engines and can also act as dynamic storage of distributed RES generation. However, as the penetration of BEVs is increasing, the management of the power demand of BEVs is becoming imperative, due to the negative impacts caused by the uncoordinated operation of EV Supply Equipment (EVSE) on the operation of power grids [10]. Several studies in the literature addressed the optimal management and sizing of BESS in the presence of distributed RES generation. A systematic review on the energy management for stationary energy storage applications is presented in [11], investigating different strategies and algorithms for the optimal operation of BESSs. Similarly, [12] presented a review of very different multi-criteria approaches for evaluating the use of energy storage systems for grid applications, by considering social, economic, technological, and environmental criteria of different types of energy storage technologies. While, [13] proposed a review on the modelling and optimization methods for controlling and sizing grid-connected energy storage systems. As stationary storage systems are mainly used to maximize the Self-Consumption Rate (SCR) of distributed RES generators, [14] proposed the simulated comparison of two different SCR increase aimed, rule-based strategies, by considering metrics assessing the efficient operation of the BESS. Other studies also considered the prioritization of loads by presenting both model predictive and rule-based control approaches aiming at maximizing the quality of service of customers, while minimizing the cost of the electricity bill. In [15], for instance, a model predictive control algorithm for PV-BESS installations is presented, aiming at minimizing the electricity bill by also implementing a series of device priorities to ensure the desired quality of service for the end user. Similarly, in [16], a rule-based load management scheme based on the classification of the criticality level of the loads was developed and tested for a residential PV-BESS installation by allowing the load prioritization and shifting based on certain rules. While [17] investigated the impact on the energy bill depending on the tariff scheme applied. More recently specific BESS management strategies have also been proposed by considering EV load demand. In [18], for instance, the simulated impact on the grid of the charging of EVs in the presence of distributed PV-BESS is presented by evaluating the rate of accelerated aging of grid components. While [19] investigated the charging process of EVs in terms of queuing time through analytical models and simulation. As it can be concluded by the presented literature analysis, even though a plethora of studies addressing the optimal management of BESS in the presence of renewables have been proposed in the scientific literature, few of them specifically addressed the use of different rule-based approaches in the presence of EV load demand. By following this research path, the aim of the present study is to compare different dispatching policies for the operation of BESSs in the presence of PV systems and EVSE. The comparison is carried out by simulating different dispatching policies for the operation of a real PV-BESS system, by considering real load demand and energy generation data and simulated EV load profiles. The remainder of the paper is organized as follows: Section 2 introduces the methodology of the study and defines the considered use case. Section 3 presents the results of the analysis, while Section 4 summarizes the main findings of the work and provides suggestions for future research.

II. MATERIALS AND METHODS

In this study, the analyses have been performed with the support of the simulation software System Advisor Model (SAM), which was developed, in 2005, by the National Renewable Energy Laboratory (NREL), in collaboration with Sandia National Laboratories [20]. This software allows to simulate the performance of a power system over the desired time, by evaluating the electricity flow from renewable energy sources (RES) equipped with battery energy storage systems (BESSs), and the grid while satisfying the users' load. SAM also proposes a financial analysis by evaluating the cash flows over the period selected based on standard or ad-hoc electricity pricing schemes (e.g., flat buy and sell rates, monthly net metering, or complex rate structures with tiered time-of-use pricing and demand charges). The reference case is the residential and office building located in the north campus of the University of Brescia in via Valotti, Brescia (Italy) – with a latitude of 45.6° and a longitude of 10.2°. In the following subsections, more details on the specific power system are provided.

A. *PV system*

The installed PV system has a nominal power of 64.34 kWp and it is made up of 279 modules connected in series in 18 strings on three different layers. The tilt angle is the same for all the layers (i.e., 15°) while the azimuth angle is 20°, 110°, and -70° for layer 1, 2, and 3, respectively. It has been also assumed a yearly degradation of the PV system of 0.8%. Data related to solar radiation, global irradiance and PV output have been extrapolated from the tool Photovoltaic Geographical Information System (PVGIS), developed by the European Commission.

B. *Power demand profiles*

The load profile was computed by considering the typical daily power demand profile of the campus over a time horizon of 1 year with a time resolution of 5 min, considering working and non-working days. The load data refer to the one year. To make them compatible with the SAM simulation, they were converted to a time resolution of an hour. Fig. 1 shows the peak power, and the electricity load profiles per month. During the summer, we can notice a significant decrease in power demand, due to the break of the lecturers.

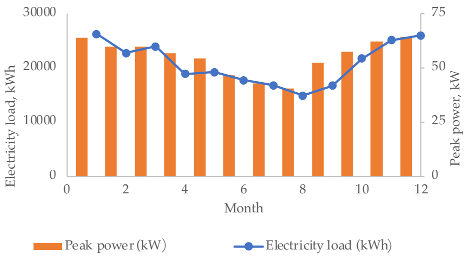

Fig. 1. Peak power and electricity load profiles per month

The four different daily profiles considered are:

- Typical Working day profile (Winter): the load increases at 9am, because students are getting ready before attending courses. Moreover, the maximum peak is measured between 6pm and 8pm, once the lessons finish, and students come back in their rooms.
- Typical Working day profile (Summer): during the summer period, it can be noticed a lower consumption, due to a lower number of students that are living in the building and the lower presence in the offices.
- Typical Non-Working day profile (Winter): it can be observed a flat consumption.
- Typical Non-Working day profile (Summer) as in Winter.

C. *Battery storage*

The PV system is equipped with a Fortelion Li-Ion (LiFePO4) battery connected to the DC side, with an energy, power, and cell capacity of 25.2 kWh, 13.8 kWp, and 24.2 Ah, respectively. The main causes of BESS capacity degradation, which affect the lifetime of the system, are the number of cycles performed at a specific depth of discharge (DOD) and the calendar aging. The specific BESS considered has an excellent cycle life: in fact, after 6000 cycles, it still has approximately 80% of the capacity.

The dispatching policies highly influences the energy flows from the grid, the PV system and the BESS also affecting the economic performance of the macro system. Specifically, in this study, five different dispatching policies have been compared:

- *Policy 1: Peak Shaving: 1-Day look ahead.* The look-ahead controller considers the forecasts of solar generation and load demand for the next day.
- *Policy 2: Peak Shaving: 1-Day look behind.* The look-behind controller operates the system by assuming that the load demand and the PV production are the same of the day before.
- *Policy 3: Automated Grid Power Target*. The users can set a maximum grid power for each period considered. The following grid power target have been set: 50 kW for January and December, 45 kW for February, March, April. And November, 40 kW for May, 30 kW for June and October, 25 kW for July and September, and 20 kW for August.
- *Policy 4: Input Battery Dispatch*. The dispatch policy operates the battery with state-of-charge and power constraints set by the user. Five hypotheses for the charging and discharging power have been analysed. Firstly, we considered that the BESS is charged during the 12 daily-hours and discharged during the night for the remaining 12 hours with a power of (i) 2kW; (ii) 5kW; and (iii) 10kW. Then, we assumed that the BESS is charged within 12 am and 4 pm with (iv) 10kW as discharging power and 50 kW as charging power; and (v) 5kW as discharging power and 10 kW as charging power.
- *Policy 5: Manual Dispatch.* The user can manually define the timing of battery charging and discharging periods differentiating up to six dispatch periods and setting weekday and weekend hourly profiles for each month. The policy that has been implemented considers three periods. In the first period (11pm - 5am), the battery can be discharge at a rate of 8% per hour, in the second period (8am - 11am), the battery can be charged from the PV system, and in third period (6am - 7am and 12am - 10pm), the battery can both be charged from PV and discharged at a rate of 8% per hour.

D. *Electric vehicles*

The campus is equipped also with AC EV charging stations of 44 kW and a Renault Zoe with an internal battery of 22 kWh. It is assumed a different number of EVs entering the system, at different timing, with an initial state of charge of 50%, a minimum SoC of the battery of 20% and a maximum SoC of the battery of 80%. In the first part of the charging process (firstly 35 minutes), the electricity flows from the charging station to the battery of the EV at the same power of 20 kW. Then, the charging power decreases until it reaches 2.5 kW (around the 70th minute), after which the power is stabilized [21]. Different hypotheses on the recharging process are compared, which differs on the number of vehicles with a simultaneous charge and the period. The first eight hypotheses consider a flat recharging process characterized by different timing. Under hypothesis (1) one vehicle arrives from 9 am to 10 am, (2) one vehicle from 12 am to 2 pm, (3) one vehicle from 9 am to 4 pm, (4) two vehicles from 9 am to 10 am, (5) four vehicles from 12 am to 2 pm, (6) two vehicles from 9 am to 10 am and two vehicles from 1 pm to 2 pm, (7) eight vehicles from 9 am to 4 pm, and (8) eight vehicles from 9 am to 10 am. In the ninth hypothesis, a real charging process is used to manage four EVs [21]: it has been supposed to charge them during the period of higher energy production of the PV system. Two EVs are charged simultaneously and the charging process of the other two starts after 70 minutes later than the first one.

E. *Economic model*

The annual differential cost of the energy system is defined by the sum of two contributions, i) one term related to the energy consumption, and ii) the other to the monthly peak power (divided by 12 since a yearly cost coefficient related to the peak power is defined), as follows:

$$Cost\ (€) = E \cdot p_e + \left(P \cdot p_p\right)/12$$

where E defines the annual energy consumption (kWh/year), p_e the energy price related to the annual consumption (€/kWh), P the maximum monthly peak (kW), and p_p the energy price related to the nominal power (€/kW).

Different hypotheses have been considered on the energy price, i.e. (i) 0.1 €/kWh, (ii) 0.15 €/kWh, and (iii) 0.2 €/kWh. At the same time, three different unit costs for the nominal power were considered: (i) 20 €/kW year, (ii) 50 €/kW year, and (iii) 100 €/kW year. Nine different combinations have been, thus, considered in the analyses.

III. RESULTS

While comparing the behaviour of the policies, different parameters have been analysed, to understand how each policy reacts to them. Specifically, the following three energy flows have been analysed: electricity from PV to load (i.e., the energy generated from the PV system to meet the load), electricity from BESS to load (i.e., the energy discharged from the BESS to meet the load), and electricity from Grid to load (i.e., the energy purchased from the Grid to meet the load).

A. *Electric vehicles*

The nine hypotheses previously defined have been analysed and compared in terms of power peak (Fig. 2) and degradation of the battery after 25 years (Fig. 3). The maximum power peak and the degradation of the battery increase for higher number of EVs simultaneously requiring to be charged and for shorter time range of the charging process, which implies higher charging power. Under the 9th hypothesis, there are 4 EVs and the charging process is completed in a larger time of period, which means lower demand peak than hypothesis 8 in which there are 8 EVs charging simultaneously in one hour. However, the remaining capacity at the end of the 25th year is lower for hypothesis 9 than hypothesis 8 (48.4% and 60.2%, respectively). This difference in the battery degradation is caused by a different number of charging-discharging cycles completed from the battery at the end of the 25th year (16,183 vs 12,599).

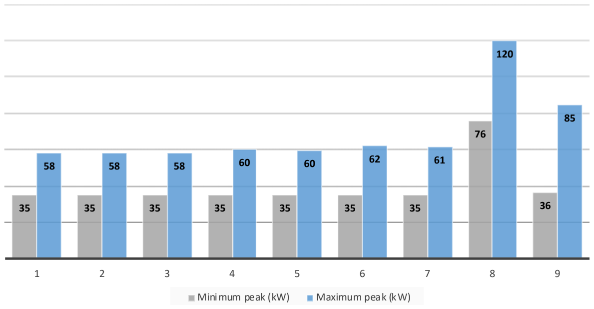

Fig. 2. Minimum and maximum power peaks under different hypotheses for the EVs’ charging process

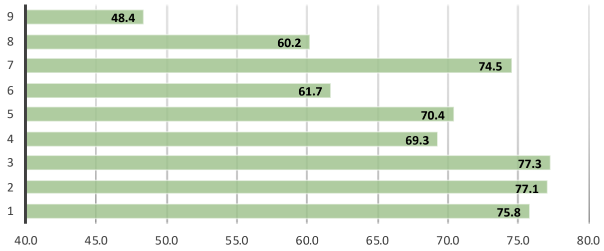

Fig. 3. Battery degradation after 25 years under different hypotheses for the EVs’ charging process

B. *State of Charge*

SAM allows to set both the minimum and maximum state of charge of the batteries. Since these parameters highly affect the performance of the storage systems by influencing the battery contribution to electricity load, the battery degradation and the demand peak, different configurations have been investigated: Configuration 1) Minimum state of charge: 0%, Maximum state of charge: 100%; 2) Minimum state of charge: 15%, Maximum state of charge: 95%; 3) Minimum state of charge: 20%, Maximum state of charge: 90%; 4) Minimum state of charge: 13%, Maximum state of charge: 97%. TABLE 1 provides the annual demand peak for the different policies investigated, while TABLE 2 the battery contribution over the electricity load. The ahead policy (Policy 1) is characterized by the lowest demand peak for each configuration (maximum peak of 52.3 kW), as the battery is used only during periods characterized by higher demand. However, it has one of the lowest BESS contributions (maximum 1.04% for configuration 1). The behind policy (Policy 2) is the worst one: bad peak shaving (maximum peak of 59.2 kW) and bad system performances (BESS average contribution under 1.01%). The automated grid power target policy (Policy 3) has intermediate system performances (BESS average contribution of 1.2%), and the battery degradation and demand peak are acceptable (23% and 58 kW, respectively). The input battery dispatch policy (Policy 4) presents the highest BESS contribution (from 2.75% to 3.18%), however, it leads to the highest demand peak (maximum peak of 59.2 kW) and average battery degradation (around 70% in configuration 3, and 50% in the others). The manual dispatch (Policy 5) presents the lowest battery degradation (around 16.9%), but on the other hand it has worse system performances (average of 1% of BESS contribution) and highest demand peak (maximum demand peak of 59.2 kW for each configuration). From the comparison of the different configurations, it can be observed that configuration 3 represents the lowest battery degradation.

TABLE 1
ANNUAL DEMAND PEAK FOR DIFFERENT POLICIES

	Demand peak (kW/month)				
	Policy	Policy	Policy	Policy	Policy

	1	**2**	**3**	**4**	**5**
Configuration 1	50.8	57.8	58	59.2	59.2
Configuration 2	51.8	59	57.9	59.2	59.2
Configuration 3	52.3	59.2	57.8	59.2	59.2
Configuration 4	51.6	58.8	57.9	59.2	59.2

TABLE 2
BATTERY CONTRIBUTION OVER THE ELECTRICITY LOAD

Configuration	**Battery contribution over the electricity load (MWh)**				
	Policy 1	**Policy 2**	**Policy 3**	**Policy 4**	**Policy 5**
1	2.59 (1.04%)	2.52 (1.01%)	3.38 (1.35%)	6.87 (2.75%)	3.18 (1.27%)
2	1.89 (0.76%)	1.89 (0.76%)	3.29 (1.32%)	7.75 (3.10%)	2.74 (1.10%)
3	1.56 (0.63%)	1.56 (0.62%)	3.06 (1.22%)	7.25 (2.90%)	2.43 (0.97%)
4	2.04 (0.82%)	2.03 (0.81%)	3.38 (1.35%)	7.94 (3.18%)	2.86 (1.14%)

One of the most significant parameters in the electrical storage systems is efficiency of the charging and discharging cycles (i.e., round-trip efficiency, η), which affects the amount of electricity losses through the system. The round-trip efficiency can be computed at the end of the simulation as:

$$\eta = 100 * abs(\frac{E_d}{E_c})$$

where E_d stands for the accumulated energy discharged, while E_c for the accumulated energy charged. This efficiency is sensitive to the average charging and discharging current. As this average increases, thermal losses increase and reduce the efficiency. The automated and input battery dispatch policies (Policy 3 and 4) present the highest efficiency (94%), while the peak shaving look behind (Policy 2) leads to the lowest efficiency (90%). The manual dispatch (Policy 5) leads to an efficiency of 93%, while peak shaving look ahead (Policy 1) of 92%. Fig. 5 shows the energy flow from BESS to load and EV (in kWh) under the different policies and hypothesis 5 for the EVs charging process.

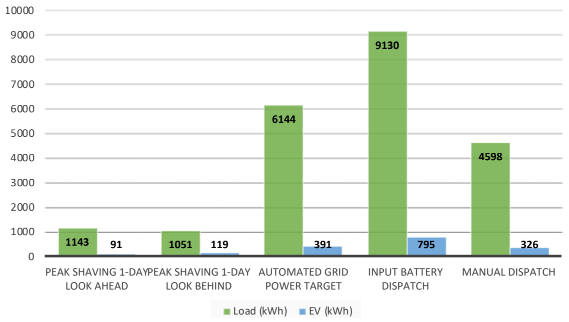

Fig. 5. Energy flows (kWh) from BESS to load and EV under different policies

C. Demand Peaks

The demand peaks under the automated policy (Policy 3) and in the range of charge [20%; 90%] are presented while considering different configurations of the system shown in TABLE 3.

TABLE 3
SCENARIOS CONSIDERED FOR THE ANALYSES

	Loads		**Generation**	
	Building	**EV**	**PV system**	**BESS**
Scenario 1	X			
Scenario 2	X		X	
Scenario 3	X	X		
Scenario 4	X		X	X
Scenario 5	X	X	X	
Scenario 6	X	X	X	X

The monthly power peaks and the average power demand for the different scenarios are depicted in TABLE 4. The only loads of the building located inside the university campus had an average demand peak of 55.1 kW and a power peak of 64.1 kW (Scenario 1). Thanks to the installation of a PV system (scenario 2), the average and the maximum demand peak can be reduced by 8% and 4%, respectively leading to an average demand peak of 50.6 kW and a maximum power peak of 59.2 kW. The integration of the BESS (scenario 4) additionally reduces them by 13% and 5% reaching an average value of 47.7 kW and a maximum value of 57.8 kW. If we include in the analysis, the 4 EVs’ loads, the average, and the maximum power peak increase by 41% and 71%, respectively. The increase is lower if the PV system (and BESS) are considered: 24% (13%) and 41% (36%).

TABLE 4
AVERAGE AND MAXIMUM POWER DEMAND UNDER THE DIFFERENT SCENARIOS

	Power demand (kW/month)					
Scenario	**1**	**2**	**3**	**4**	**5**	**6**
Max	64.1	59.2	87.5	57.8	84.7	84.5
Avg	55.1	50.6	76.6	47.7	68.1	62.6

D. Loads and generation power profiles

The following graphs show the typical day profile under different hypotheses. Firstly, it is assumed that the battery can be charged only from the PV and no EV are present in the system. Then, the 4 EVs are simultaneously introduced in the system. In Fig. 6, the energy flows are shown. The load is characterized by a peak between 4 p.m. and 22 p.m. because during that period the lessons are over, and students come back to their campus room using more consuming appliances. Due to the increase of the power demand and to the reduction of the PV contribution, the battery discharges from 4 p.m. The introduction of the EVs in the system leads to significant changes in the electricity flows. Specifically, it is possible to observe a higher peak between 12 a.m. and 3 p.m. that is the charging period of the EVs. Due to this significant change of the load flow, we have another important change in the BESS flow. In fact, the battery discharges twice because it faces two different peaks of demand. The grid flow also shows some changes due to the connection of the EVs to the charging station.

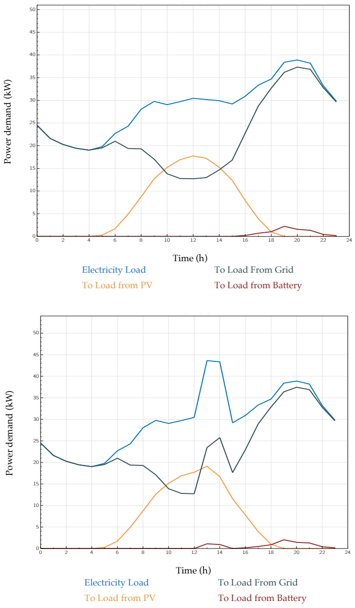

Fig. 6. Power flows in the scenario with: battery charged from PV (up) with no EV in the system, and (down) with 4 EVs simultaneously present in the system

Fig. 7, 8, and 9 provide more details on the power flows with four EVs simultaneously present in the system from the PV, the BESS, and the grid, respectively.

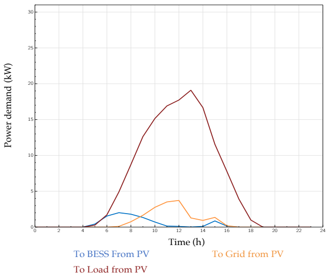

Fig. 7. PV power flows in the scenario with: battery charged from PV

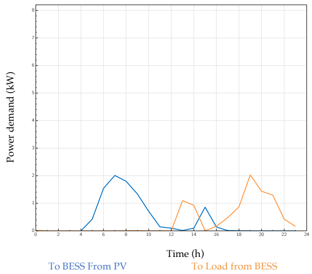

Fig. 8. BESS power flows in the scenario with: battery charged from PV

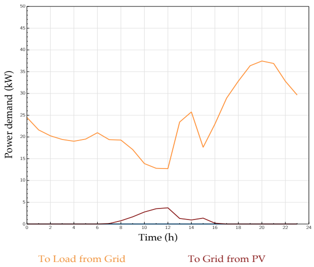

Fig. 9. Grid power flows in the scenario with: battery charged from PV

E. *Economic analyses*

The annual cost of the energy system under the different combinations of the price components (i.e., related to the energy consumption and to the nominal power) is shown in Fig. 10. Moreover, the annual cost has been assessed for three scenarios: i.e., (i) energy purchased only from the grid, (ii) from grid and PV system, and (iii) from grid, PV system and BESS. The PV system decreases the energy cost of about 23%, while the contribution of the BESS is lower and sometimes also negative (i.e., leading to higher costs). The scenario (iii) does not show any significant price changes with respect to the scenario (ii). This happened because some part of the energy produced by the PV system would not be used to meet the energy demand anymore, but it would be used to charge the BESS. However, we noticed that BESS performances increases when the nominal power price increases, and the price of the actual energy used decreases.

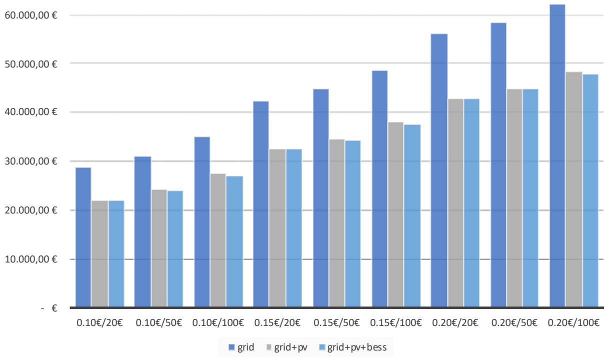

Fig. 10. Annual cost of the energy system under different combination of the price components (i.e., price related to the energy consumption/ and to the nominal power)

IV. CONCLUSIONS AND FURTHER RESEARCH

The performed analysis aimed to explain the importance of the smart management of the available renewable resources. Specifically, it is crucial to integrate and coordinate the three main elements of the system (i.e., grid, renewables, and energy storage) to increase the system performance and to incur in energy saving. The integration of a BESS into a PV and grid system has multiple applications. Each policy has its own advantages and drawbacks, and it is more suitable for specific applications. In the reference case, two goals have been pursued: to decrease the demand peaks and save energy. The reference case is a building located in the north campus of the University of Brescia), where the eLux lab is located. For this application, the Automated Grid Power Target policy, for which the users can set a maximum grid power for each period considered, resulted to be the most performant: it had a good reduction of demand peaks, and a satisfying energy support (about 1.5%). Moreover, it is a semi-automatic policy, and it guarantees an important flexibility. For what concern the admissible range of state of charge, the 20%-90% led to lower battery degradation. Later, it has been introduced the possibility to charge EVs in the system, while considering different hypotheses, characterized by different charging time and number of vehicles that are charged simultaneously. The need of charging different EVs leads to an increased energy consumption. However, the BESS were able to guarantee an important demand peaks reduction and a significant energy contribution (increasing from 1,22% to 2,3%). Finally, the PV system introduces great energy savings while the BESS contribution as energy support is very limited (around 1-3%). In fact, the main goal of the BESS is to support the reduction of the demand peaks, especially, during the EVs charging process. Further analyses can be performed on EV implementation and their charging times. Indeed, if the EVs is charged for a short period (such as 1 hour), the system will face higher demand peaks, but lower battery degradation. On the other hand, for longer charging period, the system will benefit of lower demand peaks, however the battery will be more stressed and therefore more degraded.

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