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Predictive Energy Control Strategy for Peak Shaving and Shifting Using BESS and PV Generation Applied to the Retail Sector

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Abstract: As is known, a reduction in CO_2 emissions is closely related to the improvement of energy efficiency and the increasing use of renewable energy sources in building stock due to its high contribution to worldwide energy consumption. The retail sector has become particularly interesting in this sense, because commercial buildings are no longer just places where a variety of services are offered to customers. In fact, they can be beacons of energy efficiency. In this paper, we propose a predictive energy control strategy that, through the combination of production and demand forecasting, can effectively shave and shift the peak consumption of shopping malls equipped with battery energy storage systems (BESS). The adopted optimization strategy takes into account the variability of electricity tariffs over time, as is customary in some European countries. The performed energy and economic simulations based on the experimental data collected in an Italian shopping mall clearly highlight the benefits in terms of energy and economic savings. Moreover, the reported results lead to the conclusion that BESS management, photovoltaic (PV) generation, and peak switch strategies can have a reasonable pay-back investment time even for buildings with a large energy demand.

Keywords: building energy management system; energy efficiency; renewable energy; energy storage; predictive control

1. Introduction

Current environmental and energy targets require the exploitation of renewable energy sources, reduction of energy consumption, and minimization of carbon dioxide (CO_2) emissions to alter global climate change. It is known from different studies that buildings are responsible for about 40% of the worldwide energy demand [1], with a strong trend towards electrification to meet heating and cooling needs (e.g., heat-pumps) and to couple with the transportation sector (electric vehicle charge) [2]. Focusing on the building sector, it is relevant to highlight the considerable amount of electricity consumed by the retail sector, where shopping malls represent a key example. Indeed, over the last few years, many different shops and services, previously spread throughout cities, have been gradually centralized into shopping malls. As a result, they exhibit large electrical and thermal loads and offer interesting opportunities to improve energy efficiency and to reduce CO_2 emissions. Except for architectural and structural interventions, their specific final energy uses (mainly related to lighting, ventilation, cooling and refrigeration) represent a complex system with challenging energy management requirements. For this reason, a variety of smart building energy management systems (BEMS), e.g., based on a multi-agent architecture (MAS) have been proposed in the scientific literature [3]. For instance, a specific strategy based on case-reasoning is presented in [4], where it is clearly explained that the reduction of building consumption depends not only on a proper coordination of devices (or agents), but it should take into account human behavior as well. Despite this, it is important to emphasize that energy reduction alone could not be enough to enhance suitability and to reduce the related costs significantly. For this reason, in this work we focus on how BEMS can support smart and flexible renewable-based generation and storage as for example presented in [5]. The large roof and parking lots areas of shopping malls are particularly suitable to install photovoltaic (PV) generators with a significant capacity. Currently, PV systems are the most common type of renewable energy source in the building sector due to their scalability, modularity, low maintenance needs, long effective life (more than 25 years) and fast response. The combination of lower cost and economic incentives in some countries has greatly contributed to a widespread and quick diffusion of PV generation [6]. Particularly interesting is the scenario of smart PV systems in which generation and consumption can be simultaneous, as in the case of shopping malls [7]. This implies that the ratio between the PV energy directly self-consumed on-site and produced (usually defined as self-consumption) could be as high as 100%. The benefits of maximizing the self-consumption impact directly on the amount of power drawn from the grid as well as on the energy-related costs for shopping malls. Many studies are present in the literature about the increment of self-consumption in buildings. The most common methods are based on demand-side management (DSM), on battery energy storage systems (BESS) [8] or on the optimization of PV module placement at an early design stage [9]. Different solutions can be used to store the surplus of PV generation. However, the most promising ones rely on BESS due their fast cost reduction trend. The effectiveness of the combination of PV and BESS strongly depends on the ratio between generated and consumed power over time. The application of BESS is particularly advantageous if they are used to shave and shift the peaks of consumption in buildings, thus mitigating the demand of electricity from the grid and saving money [10]. In particular, power shift is particularly useful when the cost of electricity depends on the time of the day [11]. In this respect, the actual operation of a BESS could be scheduled based on some forecasting algorithm included in the building energy management system [12]. Several works about PV power production or consumption forecasting in buildings are presented in the literature, e.g., in [13,14]. In [15] a comparison between artificial neural networks (ANNs) and support vector machine (SVMs) applied to electrical energy consumption forecasting in buildings is presented. In [16] it is shown how and to what extent a BEMS, particularly for commercial buildings, can be affected by weather forecasting inputs and can be optimized accordingly. It is interesting to note that the BEMS of a commercial building is usually centralized, and it is characterized by a broad range of scheduling options and interaction modes with the grid. Moreover, unlike residential buildings, in commercial ones the energy profiles are more strongly related to actual occupancy and ongoing activities [16]. Different forecasting methods for PV production and building consumption are presented in [17] to demonstrate how the prediction can affect the performance of PV-BES systems. In particular, the authors show that predictive control strategies may lead to higher storage revenues than real-time control ones, especially for residential buildings whenever the percentage of self-consumption increase significantly [17]. However, application to commercial buildings can lead to interesting benefits mainly if the target is not only self-consumption, but also peak-shifting. In this paper, we propose a predictive energy strategy to optimize the daily use of BESS based on both PV generation and power demand forecasting applied to the retail building sectors. The algorithm objective is to shave the peak consumption during the higher cost hours and shift it to the cheaper ones. The developed method is applied to a real case study (i.e., a shopping mall located in southern Italy), based on the measured data collected in the European project FP7-CommONEnergy [18], in order to evaluate the energy and economic advantages arising from the joint use of prediction and electric storage. The benefits of the proposed strategy will be evaluated considering energy and economic aspects. The works reported before, although obviously related to the proposed one, are different because they do not include or take into consideration all the factors that we want to investigate. For instance, the strategy proposed in [10] does not consider neither PV generation, nor load forecasting. Moreover, it does not propose to shave consumption peaks depending on electricity prices, nor an economic analysis is given. In [12] a method is proposed to use batteries for commercial building applications, by comparing different threshold computation techniques. However, a yearly economic analysis is not performed and forecasting information is not used. In [6] a comparison of different methods for energy consumption forecasting is presented and it is shown to what extent it could be useful for energy efficiency. In [11,13], even if the final goal is very similar to ours, there are the following differences. In [11] the management strategy is not based on PV or demand forecasting. In fact, it is mainly based on a demand scheduling which could be potentially (but not necessarily) supported by the battery. Moreover, the whole strategy is applied to a residential building. In [13] the evaluation of the energy management technique based on PV-BESS and solar forecasting is mainly focused on how the forecasting benefits and the forecasting error should be compensated for improving BESS sizing. However, neither an economic evaluation is performed, nor the dependence on electricity price is considered. Finally, only 2 representative months (July and November) instead of a whole year, are considered in the analysis. The rest of this paper is structured as follows. Section 2 presents the simplified electrical system and PV generation models. Moreover, the forecasting techniques used for both generation and consumption are described along with a predictive energy control (PEC) strategy. Section 3 describes the data used for PV generation and electricity consumption and defines the metrics used to evaluate, through simulations, the performance of the proposed algorithm. Several results based on experimental data collected in a real shopping mall are finally reported in Section 4, where forecasting accuracy as well as energy and economic aspects are obtained through parametric simulations.

2. Methodology

This section presents first the simplified model of the electricity system including BESS, PV, shopping mall, and BEMS which implements the PEC strategy. After that, the PV model and the methods to forecast the PV production and shopping mall electricity consumption are described.

2.1. System Model

Shopping malls due to their large demand are typically directly supplied through an alternate current (AC) bus from the medium voltage (MV) grid. When a PV system is installed on the rooftop or on the parking area this could be connected to the AC bus of the shopping mall to directly supply the energy consumption. In the considered system we assume that the PV system and the grid are in parallel with a centralized BESS, connected through a bi-directional AC-DC converter. To take into account possible losses, BESS efficiency is assumed to be equal to 90% during both charging and discharging. The simplified configuration is shown in Figure 1. It is assumed that the energy flows are monitored and controlled by a smart BEMS which collects and processes the information coming from weather, production, consumption and prices and it is able to properly control the BESS in order to shave and shift the shopping mall energy consumption peak.

2.2. PV Generation Model

The PV generation is given using a deterministic approach based on the measured global horizontal irradiance (GHI) and air temperature (T_{air}) data [19]. This approach consists of a chain of three physical models:

1. A decomposition model to retrieve the direct normal irradiance (DNI) and the diffuse irradiance (DHI) from the GHI data. In this case, the direct insolation simulation code (DISC) model has been applied [20–22]. DISC is very simple model that provides the DNI using only the global horizontal and the extraterrestrial direct normal irradiance [23]. The DHI is then simply computed from the GHI and the estimated DNI.
2. A transposition model to retrieve the global irradiance on the plane of array, i.e., the tilted irradiance (GTI). Here, the isotropic model developed by Liu–Jordan is used [24]. This is one of the most common method when only DNI, DHI, and albedo are available.
3. Last step is given by a power estimation model to convert the incident irradiance into PV generation. For this purpose, the Sandia array performance model (SAPM) developed in [25] has been chosen. This is one of the most accurate models to estimate the PV power because it takes into account all the main performance losses that affect the PV performance in real operating conditions.

Using this procedure, the power generated by a PV plant has been estimated. This virtual PV plant has been placed on 30 degree tilted and South oriented surface since this is the plane of the array that maximizes the production [26].

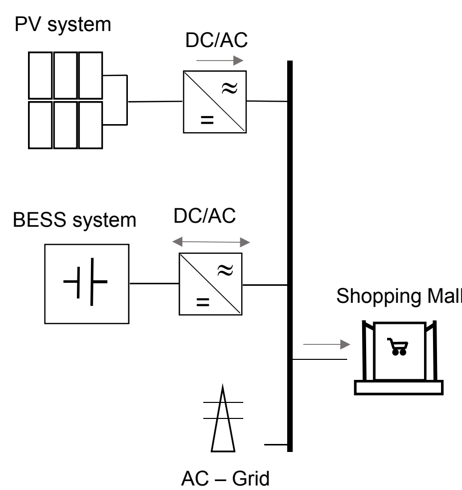


Figure 1. Simplified system model composed by: photovoltaic (PV) and battery energy storage (BES) system, shopping mall and electric grid.

2.3. PV and Electrical Demand Forecasting

The optimal BESS schedule is based on one day-ahead forecast: the PV power production and the shopping mall power demand. In the first case, the PV power forecast (PV^{for}) is obtained applying the procedure described in Section 2.2 to the numerical weather prediction (NWP) of the GHI and T_{air}. In the second case, for the day-ahead forecast of the electric demand ($Load^{for}$), the persistence model has been used. This simple model assumes that the load of the next day is equal to the load of the previous day. In particular, for the working days a day-ahead persistence is used while for the Sundays and holidays a weekly persistence is adopted (Equation (1)). In particular, we have:

$$Load^{for}(dd+1|\, dd-ndd, h) = Load(dd-ndd, h) \quad (1)$$

where dd is the actual day, h is the hour of the day, ndd is the number of past days with respect to the actual day used in the persistence model and $Load$ is the actual electricity demand. Despite the use of a simple model, in this case the persistence exhibits good accuracy due to the fact that the electricity demand exhibits significant changes during the month, but slow variations from day to day.

When a PV plant is also considered, the electric demand changes according to the solar generation and the residual demand ($NetLoad$) results from the difference between the load and the PV production. Thus, the day-ahead forecast of the $NetLoad$ could be easily obtained from the PV power and load predictions according to:

$$NetLoad^{for} = Load^{for} - PV^{for} \tag{2}$$

In this case, due to the above consideration it is clear that the day-ahead $NetLoad^{for}$ variations will mainly depend on the PV^{for} behavior since the $Load^{for}$ exhibit smaller changes in subsequent days.

2.4. Predictive Energy Control Strategy

The PEC strategy is used to optimize the use of the BESS to shave and shift the shopping mall demand. This strategy considers three aspects:

1. electrical system characteristics (e.g., maximum and minimum state of charge, maximum and minimum power from/to BESS, converter and battery efficiency);
2. accurate availability of PV production and electricity demand forecast;
3. dependency between daily hours and cost of the energy drawn from the grid. In particular, currently in Italy there are three time of use tariffs indicated as *F1*, *F2* and *F3*. The first two tariffs cover the morning and afternoon of working days and are more expensive, while the third one is cheaper, and it is applied for evening and holidays.

With respect to these three aspects, the aim of the PEC is to shift the $Load$ (or $NetLoad$ when PV production is present) from hours of higher electricity price to hours of lower electricity price and at the same time, shave the power peak of the consumption. The PEC provides two control actions: predictive and operative.

The predictive strategy finds for each day the maximum power that could be provided by the BESS and sets a defined power threshold. This threshold (S) is computed by an optimization procedure, presented in Figure 2 on the left, imposing that the energy difference between the $NetLoad^{for}$ and the threshold should be equal to the effective storage capacity. At the same time, the solar energy exceeding the day-ahead consumption that can be used to charge the storage (solar recharging energy) is predicted. Thus, knowing the effective capacity and the solar recharging power, the amount of power from the electricity grid that should be used during the night to recharge the storage (grid charging power) can be computed following the steps shown on the right Figure 2.

The operative strategy aims to control the BESS using the predicted information. First, electricity from the grid is used to recharge the storage during the night. Then, discharging the storage during the day, the peak of $NetLoad$ is shaved at the power threshold level and at the same time, the storage is (eventually) recharged with the PV power that exceeds the electric demand. The BESS management is limited by the battery maximum charging and discharging power. The flow-chart of the operative strategy is reported in Figure 3, where NL and NL_{shave} are the current and shaved $NetLoad$. The other quantities have been already introduced in Figure 2.

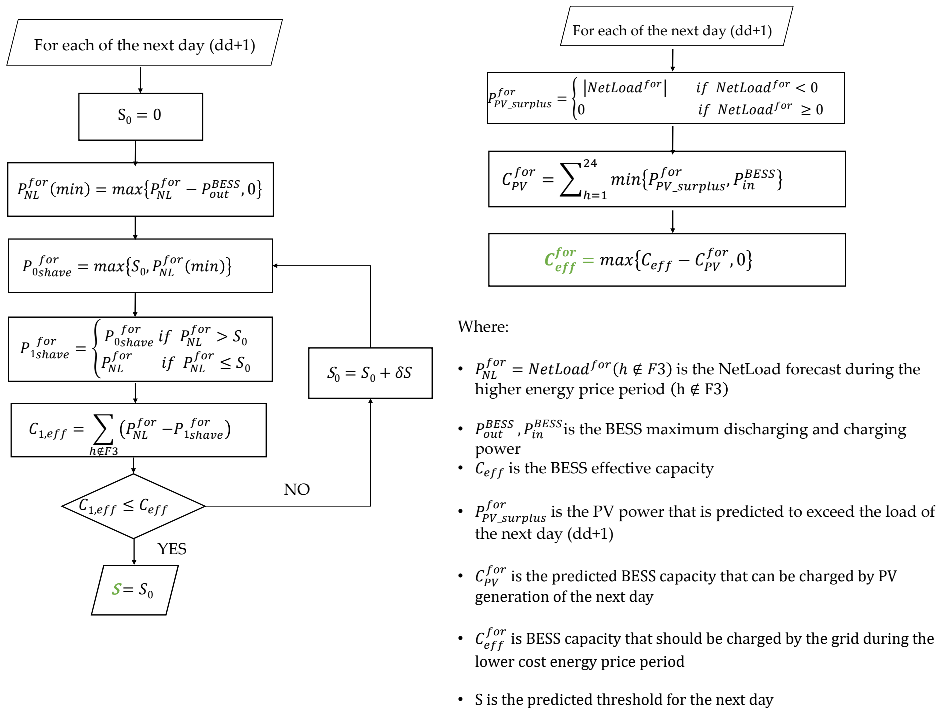


Figure 2. Algorithm for the predictive strategy based on the threshold optimization (on the left) and forecast solar energy to charge the battery energy storage systems (BESS).

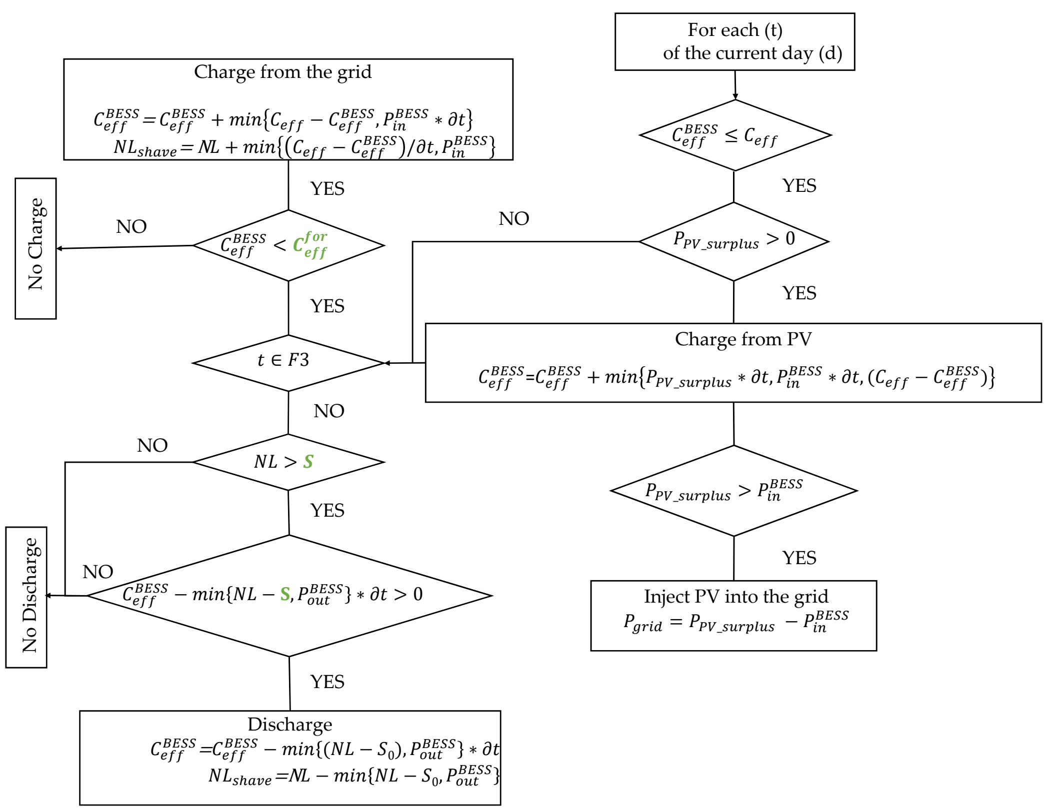


Figure 3. The flow-chart of the proposed operative energy control strategy.

The behavior of the proposed algorithm is represented in Figure 4. In particular, Figure 4a shows an example of one-day power profile, where 1 MWh of effective BESS capacity is considered. It is possible to note that, during the hours with the high electricity price (in gray area), the load peaks exceeding the threshold (i.e., gray line) are cut by using the power from the battery (red area), while during the hours of low energy price the storage is charged with the power from the grid. The actual demand profile in black line is predicted by the dashed line ($Load^{for}$) which after the PEC application and the properly use of the BESS becomes the shaved and shifted profile in green. Similar results are obtained in Figure 4b where a 1 MWp of PV nominal power is also considered. In this case, the PV production (yellow curve) heavily reduces the electric demand. Thus, in this case, the storage is still charged during the night hours as in Figure 4a.

It is important to remark that this strategy has been properly proposed for countries such as Italy, where different electricity prices are present during the daily hour.

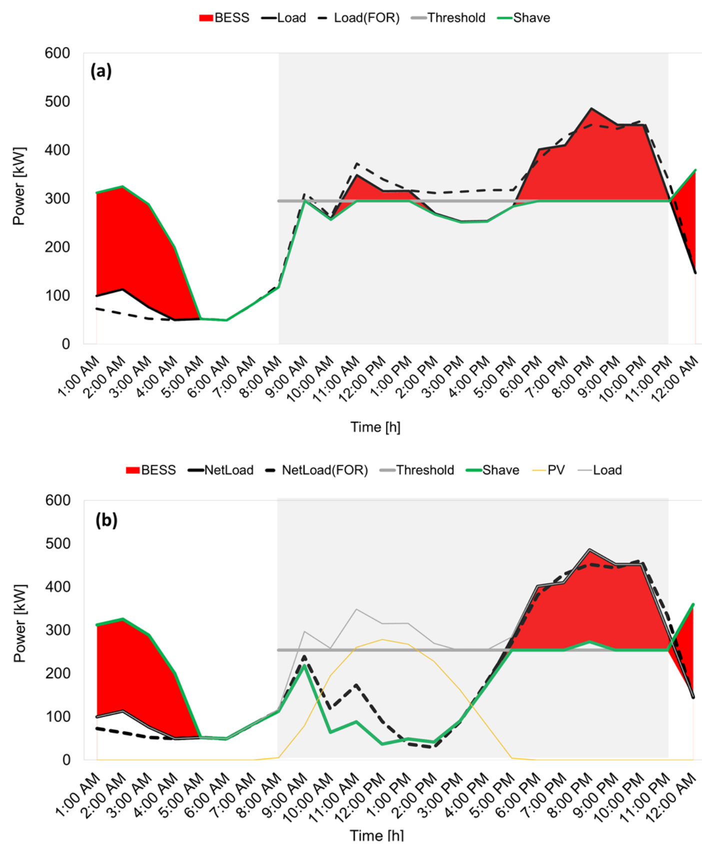


Figure 4. Examples of load shaving obtained using the predictive energy control (PEC) strategy: (**a**) Only BESS is present; (**b**) Both BESS and PV system are present.

3. Simulation Parameters And Metrics

Several simulations have been performed to evaluate and quantify the validity and the benefits of the proposed technique, in terms of energy and economic impact. Key performance indicators (KPIs), defined in the following, have been computed on the data and information provided from a real shopping mall located in the South of Italy. The shopping mall is one of the reference building analyzed in the

European FP7 project CommONEnergy [18]. This section introduces the data, the metric definitions and the parameters used in the following simulations.

3.1. Consumption and Weather Data

The electricity demand is referred to the common areas of the considered shopping mall. In particular, the measured data are the hourly consumption over the year 2014, where the lighting system contributes for about 39% while the air conditioning and ventilation system for about 51% of the total demand. Other electric equipment and refrigeration contribute for the remaining 10%. The overall annual electricity demand is estimated around 2915 MWh and a detailed analysis of the average, maximum, and minimum values can be found in [18].

The NWP used to forecast the amount of PV power available in the area where the shopping mall under study is located was performed by IDEAM S.r.l., a company which offers weather monitoring and forecasting services. In particular, the NWP of irradiance and ground air temperature are generated by the weather research and forecasting model (WRF ARW) version 3.6.1 developed by National Center of Atmospheric Research (NCAR). WRF ARW is run operationally by the U.S. National Weather Service and it is one of the most used models around the world for research and weather forecasts [27]. Daily hindcasts are performed for the considered period. The model has been initialized at 12 UTC, analyzing the 24 h forecasts starting from the following 00 UTC, which is the typical procedure for the NWP day-ahead forecast. The model domain is centered over Italy with a horizontal resolution of 12 km, a higher resolution inner domain is nested centered on the region of interest, with a horizontal resolution of approximately 3 km. The resolution time of the model is one hour.

3.2. Key Performance Indicators

The forecast accuracy is evaluated using the root mean square error ($RMSE$) defined as:

$$RMSE = \sqrt{\frac{\sum_{h=1}^{N_h}(X_h^{for} - X_h^{obs})^2}{N_h}} \tag{3}$$

where N_h is the number of hours in the considered year for the load accuracy evaluation, while for the PV generation is the number of sun hours always in the considered year. Moreover, X^{FOR} and X^{obs} are the forecast and the observed actual value of the variable X. To evaluate the amount of energy shaved and shifted by BESS system (and PV when available), we defined the peak shaved (PS) index as:

$$PS_{\%} = \frac{\sum_{h=1}^{H}(PS_{F1} + PS_{F2})}{\sum_{h=1}^{H}(Load_{F1} + Load_{F2})} \times 100 \tag{4}$$

where PS_{F1} and PS_{F2} indicates the energy shaved in *F1* and *F2* electricity fees over the total demand during the same time slots ($Load_{F1}$ and $Load_{F2}$).

The performance of the PEC strategy has been also evaluated from an economic point of view. This is an important aspect to consider, because even when energy savings are possible, economic profitability is not always guaranteed, since it depends on both local electricity tariffs and national regulations [28]. Therefore, in order to quantify the economic impact, several metrics are considered and defined in the following paragraphs. First of all, as direct consequence of the PS index, the money saved for each energy tariffs (i.e., Ms_{F1}, Ms_{F2}, Ms_{F3}) have been defined in presence of the current regulatory framework, e.g., net-metering rule (N_m) and surplus remuneration (S_{PV}). In particular, in Italy net-billing/net-metering ("scambio sul posto") is available up to a PV system size of 500 kWp. If the yearly PV production is higher than the energy consumption, the annual net energy injected into the grid is considered to be surplus. Thus, the total money saved index (MS_{tot}) is given by:

$$MS_{tot} = Ms_{F1} + Ms_{F2} + Ms_{F3} + N_m + S_{PV} \tag{5}$$

The total capital expenditures ($CAPEX$) per unit of power rating for both PV and BESS (i.e., $CAPEX_{PV}$ and $CAPEX_{BESS}$) is given by:

$$CAPEX_{PV} = C_{PV} \times P_{PV_{nom}} \tag{6}$$

$$CAPEX_{BESS} = (C_{PCS} + C_{BOP} + C_{BESS}) \times C_{eff} \tag{7}$$

where C_{PV} and C_{BESS} are the cost of PV and battery for PV nominal power ($P_{PV_{nom}}$) and effective capacity (C_{eff}) respectively, while C_{PCS} and C_{BOP} considered in the BESS investment are the cost of power converter system and balance of the power according to the definition given in [29].

To compute the levelized cost of energy ($LCOE$) over the PV life time period (LT_{PV} i.e., assumed 30 years), we need to take into account the cost of battery replacement (CR) during this period. Based on the literature, it is reasonable to assume the cost of battery replacement half of the initial price [30] and widespread this cost over BESS life time (i.e., 8 years). The resulting replacement cost (CR) can be expressed as:

$$CR = \frac{C_{BESS} \times C_{eff}}{2 \times LT_{BESS}} \tag{8}$$

which indicates that the cost of replacement is about the half of the initial cost. Assuming that the system will work for several years, the operating expenditure costs should also be defined to obtain an accurate computation of the $LCOE$. In particular for PV and battery system the operative expenditure ($OPEX$) cost are:

$$OPEX_{PV} = C_{PV_{O\&M}} \times P_{PV_{nom}} \tag{9}$$

$$OPEX_{BESS} = (C_{BESS_{FO\&M}} + C_{BESS_{VO\&M}} \times N_{cycle} \times N_h) \times C_{eff} + CR \tag{10}$$

where the $C_{PV_{O\&M}}$ is the operation and maintenance cost for PV, while $C_{BESS_{FO\&M}}$ and $C_{BESS_{VO\&M}}$ are the fixed and variable operation and maintenance costs for BESS, multiplied for the BESS cycle number over the year N_{cycle} and the operative working hours over the day N_h. The formula of $LCOE$, given in [31] and properly adapted to the presence of battery system, is given by:

$$LCOE = \frac{(CAPEX_{PV} + CAPEX_{BESS}) + \sum_{t=1}^{LT_{PV}} \left[\frac{OPEX_{PV}(t) + OPEX_{BESS}(t)}{(1+WACC_{nom})^t} \right]}{\sum_{t=1}^{LT_{PV}} \left[\frac{Yield(0)(1-Degr)^t}{(1+WACC_{real})^t} \right]} \tag{11}$$

where $WACC_{nom}$ is the nominal weighted average cost of capital per annum, $WACC_{real}$ is the real weighted average cost of capital per annum, $Degr$ is the annual degradation of the nominal power of the PV system and $Yield(0)$ is the initial annual yield in the first year without degradation.

To complete the economic analysis, the simple pay-back time (PBT) is also considered. In particular the PBT, quantifies how many years are required to cover the initial investment costs considering the annual benefits. The simple PBT, as shown in [32], is one of the most commonly used indexes to evaluate the profitable PV and BESS system in building and in our case we define it as:

$$PBT = \frac{(CAPEX_{PV} + CAPEX_{BESS})}{[MS_{tot} - (OPEX_{PV} - OPEX_{BESS})]} \tag{12}$$

To conclude, we report in Table 1 the considered input data for the simulation of the analyzed year. It is worth highlighting that the cost of PV system, the cost of battery and the $O\&M$ cost, both for PV and BESS, are averaged costs collected from the literature [29,31]. Meanwhile, for the electricity prices we refer to the cost of "prezzo unico nazionale" (PUN) referred to the year 2014 [33], the same of the measured data, plus fixed cost.

Table 1. Input parameters used in the simulations.

Name	Value	Reference
Cost electricity—F1	0.168 €/kWh	[33]
Cost electricity—F2	0.166 €/kWh	[33]
Cost electricity—F3	0.125 €/kWh	[33]
Net-billing	0.100 €/kWh	-
Surplus	0.05 €/kWh	-
Photovoltaic (PV) system	1200 €/kWp	[31]
Battery energy storage systems (BESS)	570 €/kWh	[29]
$O\&M_{PV}$	19 €/kWp	[31]
$O\&M_{BESS}$	4.63 €/kWp	[29]

4. Results

This section will show the results of the proposed PEC technique. First, an accuracy analysis of the PV power and electricity demand forecast has been reported. This is fundamental to highlight how the chosen forecasting techniques can impact on the goodness of the PEC strategy. After that a parametric analysis considering different size of PV system and BESS over a complete year has been performed in order to appreciate the behavior of peak-shaving, money saving, and PBT and LCOE areas. These results will lead to identify the one of the best size of PV nominal power and BESS capacity for the analyzed case study. Assuming this configuration, the specific case is analyzed in detailed indicating advantages in term of energy saved and economic costs and how the production and demand forecasting impact on the BESS management. Finally, a comparison between the proposed PEC strategy and the basic approach described in [7] is provided.

4.1. PV and Electrical Demand Forecasting Accuracy

In Table 2 the day-ahead forecast error of the load, PV generation, and netload are reported. The load forecast shows an accuracy of 39.61 kWh, while the PV power forecast model has a much lower accuracy of 90.13 kWh. The differences in performance between the two forecasts can be explained in the different difficulty in the prediction. The load trend has a quite simple statistical behavior that can be easily predicted also with a simple model like the persistence. On the contrary, to forecast the stochastic meteorological behavior a very complex NWP model is needed, so that a lower accuracy is actually reached. Obviously, the accuracy of the netload forecasted is in between of the accuracy of the load and PV generation predictions with an error of 51.96 kWh. Figure 5 reports the actual and the forecast time series of the load, PV, and netload. Beyond the agreement between observed and predicted values, it shows that 1 MW PV plant can completely supply the electrical demand during the sun hours.

Table 2. Correlation index (Corr), mean values (Meas) and root mean square errors (RMSE) of load, photovoltaic (PV) and netload for day-ahead predictions.

	Corr.	Mean [kWh]	RMSE [kWh]
Load	0.98	284.54	39.61
PV	0.92	363.98	90.13
NetLoad	0.96	218.52	51.69

4.2. Parametric Simulation Results

To study the energy and economic effects of the PEC algorithm, several simulations at different BESS effective capacity (C_{eff}) and PV nominal power ($P_{PV_{nom}}$) have been performed. C_{eff} ranges from 10 kWh to 2500 kWh while the $P_{PV_{nom}}$ ranges from 10 kWh to 2000 kWp. The parametric analysis is useful to understand which reasonable capacity values could be installed on the considered shopping mall.

Figure 6a reports the ratio of the energy from the grid with respect to the load during the higher price period, i.e., the load PS. The maximum of PS is around 89% at the maximum capacity values. Nevertheless, after 1 MWp of PV the surface starts to increase with the PV capacity much more slowly, thus the best cost-benefit PV nominal power should be around this value (the knee of the surface). On the contrary, the PS surface increases linearly with the effective capacity of the storage. Figure 6b shows the money saved obtained by the shift of the grid energy consumption, the PV generation self-consumption and the revenue due to PV power injected into the grid. In this case, the surface is almost a plane and the maximum gains is 431 k€/year. Figure 6c points out the PBT of the investment. It cannot exceed lifetime of the PV plant (gray line). The PBT it is very high at low PV capacities since the actual cost of the BESS are still too high with respect to the economic revenue. Nevertheless, the surface rapidly decrease with the increase of the PV capacity. This depends on the PV generation and load simultaneity, so that the netload is considerably reduced during the high price hours and at mean while the PV production eventually exceeding the consumption can both refill the storage (saving also the costs of the batteries recharging in the night time) and inject into the grid. In these conditions, the BESS could easily shave the remain netload with an increased cost-benefit until 500 kWh of BESS and 500 kWp of PV. After these values the PBT surface is a slowly increasing plane between 4.6 and almost 10 years. Finally, Figure 6d shows the LCOE that should be compared to the price of the saved energy: 0.168 €/kWh (gray line). The slope of the LCOE is similar to the PBT, since reflect the same economic revenue. The red points in Figure 6 represent the energy and economic benefit that can be obtained installing a plant of 1000 kWp of PV and 500 kWh of BESS (on the knee of the PS surface). In this case it will be possible to obtain 55.7% of PS, 238 k€/year of revenue, 6.8 years of PBT and a LCOE of 0.079 €/kWh that is less than the half of energy fee during the high price hours (0.168 €/kWh). This solution is chosen also taking into account the physical constrains of the considered mall such as the available surface for the PV plant installations.

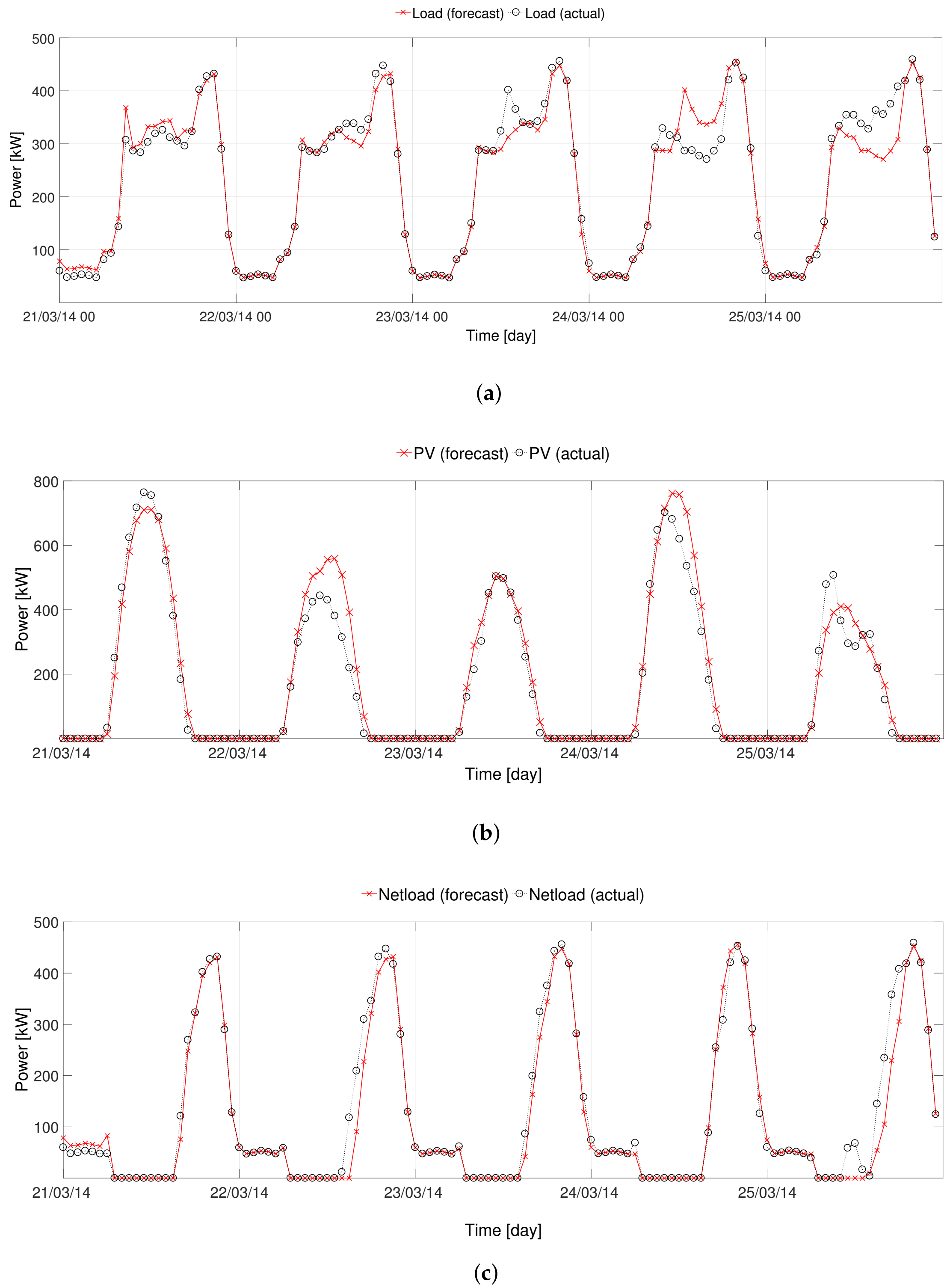


Figure 5. Actual and forecasted five-days power profiles of (**a**) load; (**b**) PV and (**c**) NetLoad respectively.

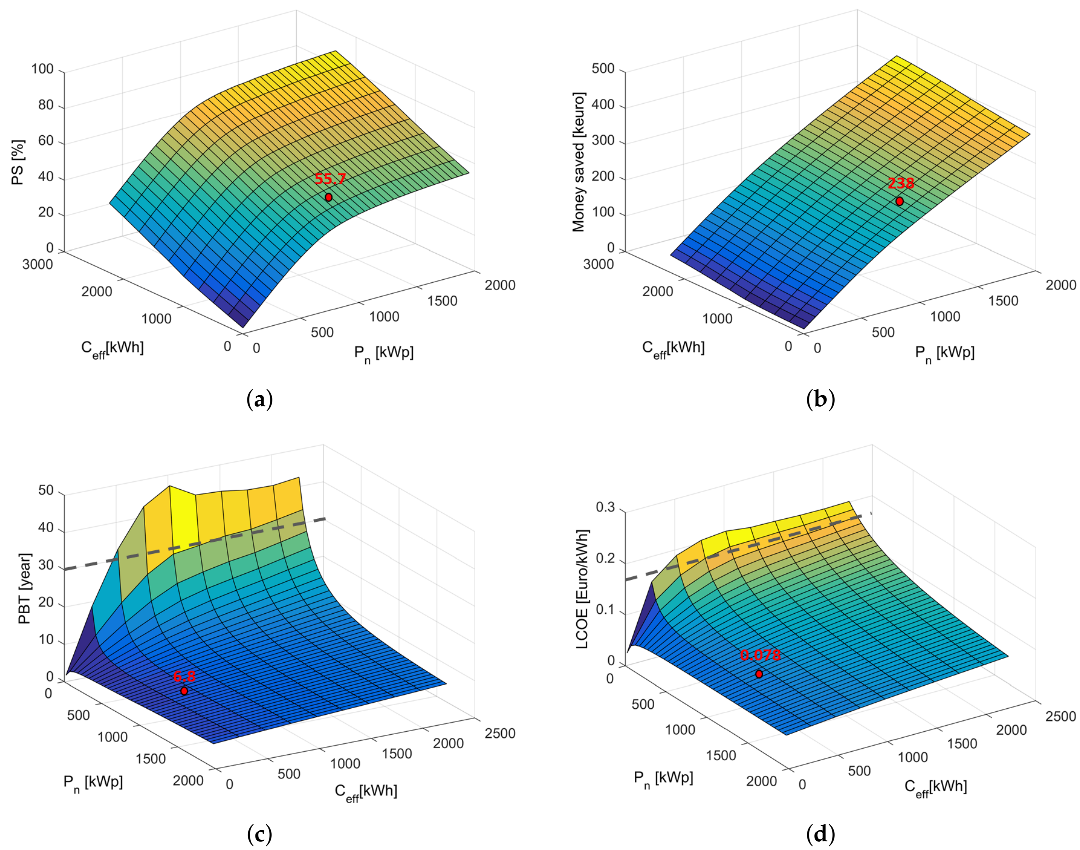
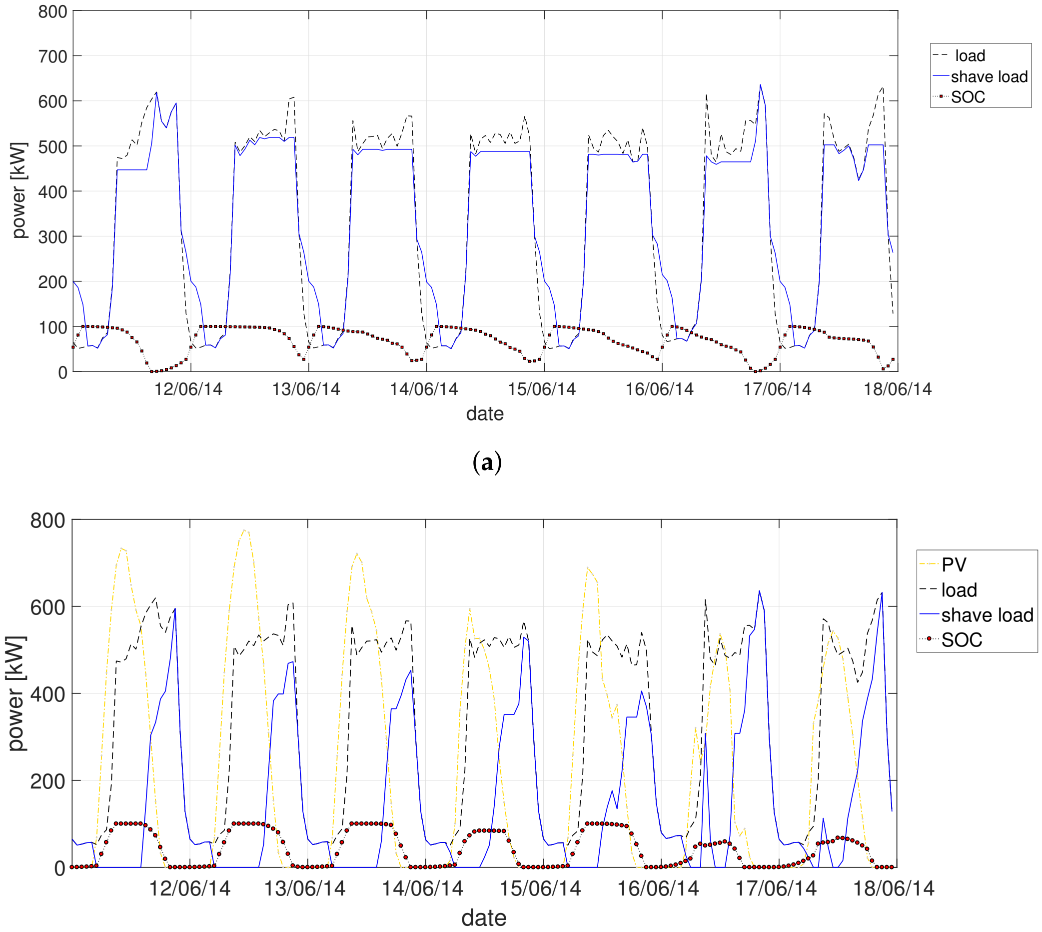


Figure 6. Energetic and economic effect of PEC: (**a**) Percentage of peak shave with respect to the load (PS); (**b**) Money saved; (**c**) Pay-back time (PBT); (**d**) Levelized cost of energy (LCOE).

Figure 7 shows the week time series of the load and of the shaved load together with the state of the charge (SOC) of the battery storage both in the case of 500 kWh BESS (up) and in the case of 500 kWh BESS and 1000 kWp of PV. It helps to better understand the operative behavior of the PEC algorithm.

When only the BESS is used, the load should be shaved to the threshold level until the batteries are completely discharged (SOC equals to SOC_{min}) and then the storage should completely charge in the night (SOC equals to SOC_{max}) Nevertheless, there are some days during which the SOC do not reach the zero value (from 13 to 16 of June). This depends on the load forecast errors. Indeed, if the daily load is overestimated, which means mean bias error (MBE) > 0, also the power threshold is overestimated so the storage will not be completely discharged. On the contrary, if the daily load is underestimated by the forecast (i.e., $MBE < 0$), the threshold is lower, thus in principle, the storage should be fully discharged. Nevertheless, if the main underestimation is during the last hours of the day, the storage could not have enough time (during the high energy price period) to be completely discharged. In case the BESS is combined with PV system, the load is completely shaved and the charge storage is fully restored. Indeed, the load is zero and the SOC is SOC_{max} during almost all the sun hours. Moreover, the storage will not recharge during the night hours (i.e., SOC remains SOC_{min}) this indicates that the PEC predicts for the next day enough PV production to supply both the load and the storage system, respectively. Even in this case, the forecast error can cause incomplete battery cycles.



(**a**)

(**b**)

Figure 7. Weekly time series of load, shaved load and state of the charge (SOC): (**a**) With only 500 kWh of BESS; (**b**) With 500 kWh of BESS and 1000 kWp PV plant.

Nevertheless, the forecast accuracy has a small impact on the effective use of the BESS because only 18% of the days incomplete battery cycles can be observed and in these cases the SOC ranges from 10% to 30%, as shown in Figure 8 where the percentage of incomplete battery cycles over the year is reported. This suggests that the provided forecast can be considered enough accurate for this application. Figure 9 shows the monthly average of the effects of the proposed algorithm assuming only 500 kWh of BESS (Figure 9a) or 500 kWh BESS with 1000 kWh of PV (Figure 9b) respectively. In the first case, using the BESS, the energy consumption from the grid is shifted from the period of high electricity price to the period of low electricity price. Indeed, the storage is discharged from 7 h to 23 h (green area), shaving the load peak, while is charged from the 23 h to 7 h (red area) increasing night consumption. In the second case, the PV generation almost completely supplies the energy consumption during the sun hours while the BESS reduces the load till 23 h of the night. Furthermore, the PV plant also provides almost all the energy to charge the battery. Only from August to December a small amount of energy from the grid is needed to restore the capacity of BESS.

Table 3 summarized the energy and the economic benefits resulting from the PEC considering the case of 500 kWh of BESS and 1000 kWp of PV. The PEC technique reduces the demand during the higher electricity prices (F1 and F2) of 1249 MWh per year, while increases the consumption of low electricity price (F3 fee) of only 26 MWh per year. At the same time, the PV plant injects into the grid 317 MWh that is about 20% of the total yearly production (1542 MWh), which is the exceeding energy not used for load shaving neither storage charging. The load shaving and the PV surplus lead to an economic saving of 238 k€ per year.

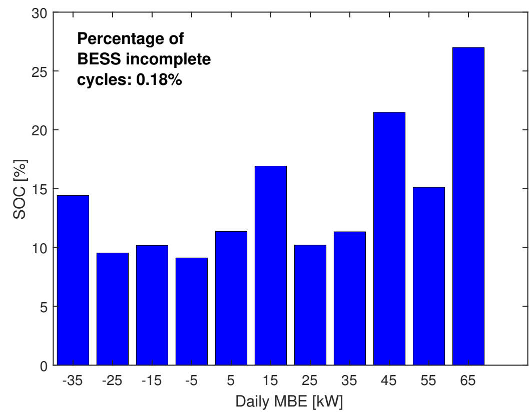


Figure 8. Number of incomplete cycles due to Netload forecast errors (daily mean bias error (MBE)).

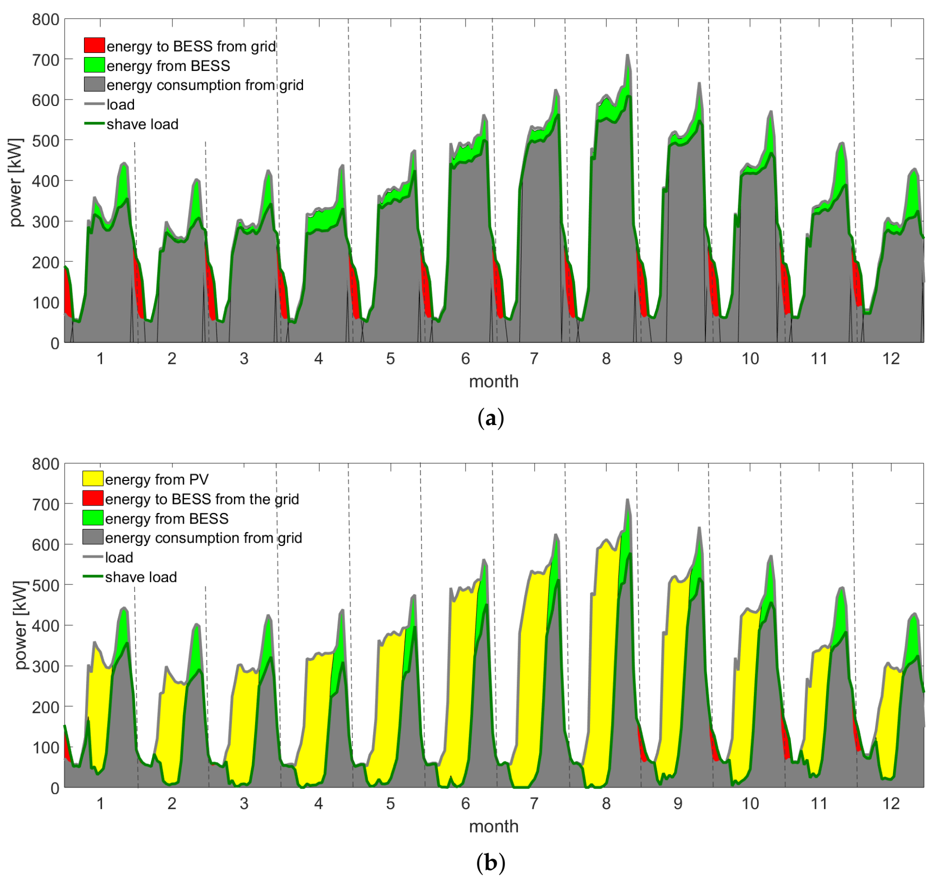


Figure 9. Monthly average of the daily energy and power profiles needed to fulfil the electric demand before and after the peak-shaving: (**a**) with only 500 kWh of BESS; (**b**) with 500 kWh of BESS and 1000 kWp PV plant.

Table 3. Energy and Economic gains. In brackets, the percentage of shaved or PV energy.

Energy Fee	Load [MWh/year]	Shave Load [MWh/year]	Energy Shaved [MWh/year]	Saving [k€/year]
F1	1552	459	−1093 (−70%)	183.6
F2	691	535	−156 (−23%)	25.8
F3	216	242	26 (12%)	−3.25
Surplus	0	0	−317	31.7
Total	2459	1236	−1540	237.85

Finally, Table 4 provides a summary of the economic parameters and of the economic results for the considered BESS and PV plant. The capital expenditure (CAPEX) of the BESS is 430 k€ , i.e., 860 k€ per MWh of installed battery storage while the PV CAPEX is 1200 k€ per MWp of installed capacity. This results in a total investment of 1630 k€. Thus, considering the economics savings reported in Table 3, the simple PBT of the investment is 6.8 years.

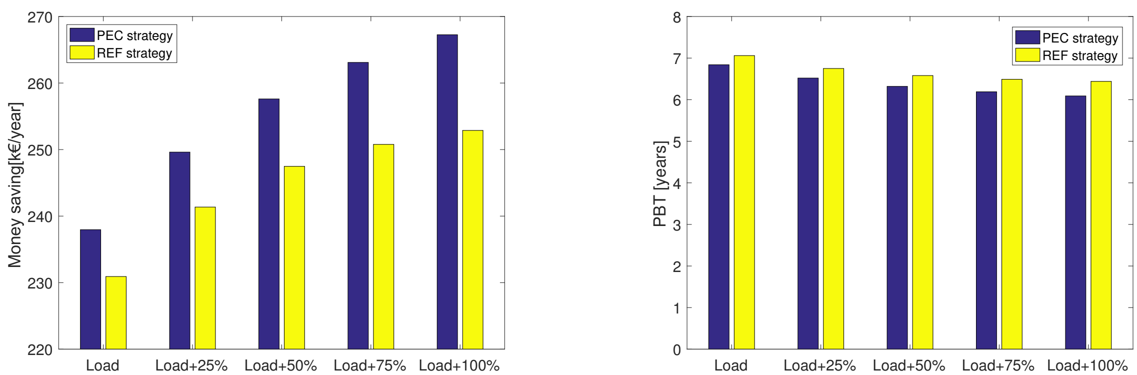
The operating expenditure of the BESS is 3.5 k€/year (considering 365 cycles per year and 20 discharging/charging hours per cycles) i.e., 8.6 k€/year per MWh of nominal installed capacity or 29 k€/year per MW of battery nominal power. The OPEX of the PV is 19 k€/year per MWp of installed peak power, which is 1.6% of the CAPEX. Furthermore, the considered replacement cost (CR) of the battery storage is 26.86 k€/year spread over 8 years (the BESS life time) which is the half value of the initial cost (i.e., 430 k€per year). Each 8 years the CR is halved until the 30th year that is the life time of the PV plant. Using these costs, a LCOE of 79.2 €/MWh is obtained. This LCOE is lower than the half of the energy fees F1 and F2 (Table 3). Thus, demonstrates that use of this PEC to manage the BESS and the PV plant for this specific application is quite profitable.

Table 4. Summary of economic parameters and results.

Parameters	Values
CAPEX BESS:	430 k€
CAPEX PV:	1200 k€
Investment:	1630 k€
Pay-back time (PBT):	6.8 years
Replacement cost:	22.3 k€/year
OPEX BESS:	3.5 k€/year
OPEX PV:	19 k€/year
Levelized cost of energy (LCOE):	79.2 €/MWh

4.3. Comparison of PEC Strategy with a Reference Algorithm

For the sake of completeness, in this section we present a comparison between the proposed algorithm (PEC) and a simple reference strategy (REF) based on the use of BESS to maximize PV self-consumption. In the reference strategy, the PV generation is firstly used to meet the building demand and then, in case of a surplus, the PV power is stored into the battery whenever the SOC level is lower than SOC_{max}. In addition, as soon as the battery is full, the PV surplus is injected into the grid. Conversely, when the PV production is not enough to meet the demand, first the battery is discharged and then the power is drawn directly from the distribution grid. The strategy is common to maximize PV production and a simple application for buildings is reported in [7]. It is important to highlight that neither PV nor load forecasting is considered at all in this case. Also, any dependence on electricity prices is disregarded. Simulations based on both strategies have been performed assuming that the electricity demand grows in the range 25%–100%. This scenario could be realistic because, as described in Section 2.1, the total electricity demand of a shopping mall depends not only on the common areas, but also on the activities in shops, supermarkets, and food districts. Results about money savings and PBT are reported in Figure 10 to compare the economic profitability and the return on investment. For both strategies, the same parameters previously presented in this paper are considered. Also, to be consistent with the previous analysis, the PV peak power and BESS capacity are assumed to be the same as before, i.e., 1000 kWp and 500 kWh, respectively. Figure 10a shows that when the load increases, the economic revenues grows accordingly, as expected. The trend is almost linearly and similar for both techniques. However, the PEC strategy clearly exhibits a larger benefit in terms of money savings, with an increment by 12% when the load is 100% bigger. Conversely but consistently, the PBT of both algorithms shown in Figure 10b exhibit a decreasing trend when the load increase. However, the return on investment is shorter when the PEC strategy is used. The plotted results confirm the validity and the better performance of the presented strategy compared to the reference case, in which instead the BESS is simply discharged when needed. Moreover, the trends in Figure 10a,b show that the PEC strategy is increasingly profitable when buildings with a large energy demand are considered, which is exactly the case of shopping malls.



(**a**) (**b**)

Figure 10. Results of (**a**) money savings and (**b**) simple pay-back time; for the proposed PEC and reference strategies respectively, increasing the electricity consumption.

5. Conclusions

Residential and commercial buildings contribute to total worldwide electricity consumption significantly. For this reason, increasing their energy efficiency maximizing the exploitation of renewable energy sources is essential to reduce CO_2 emissions. It has been demonstrated that a proper BEMS can reduce energy demand by at least 50%, especially if advanced monitoring and control strategies are implemented. In this work, we propose a PEC strategy to shave and to shift the peak power demand in shopping malls, which are probably the most power-hungry buildings in the retail sector. The proposed technique tends to optimize the use of BESS through demand and production forecasting, while taking into account both the time-varying price of electricity during the day and the energy self-generated by local PV generators.

The proposed control strategy has been tested in simulations using experimental data collected in a shopping mall located in Italy. The results in the considered case study highlight that if PV generators and storage systems of considerable capacity are installed, it is possible to shave energy consumption up to about 55%, when the price of electricity from the grid is maximum. Moreover, predictive control becomes even more profitable when the storage system, can be fully charged by the available PV generators. To complete the analysis, an evaluation of the impact of forecasting accuracy is also provided. This analysis leads to the conclusion that even when simple forecasting methods are applied, the uncertainty due to production and demand provision does not significantly affect BESS management. Finally, a comparison with a reference energy management system shows that the proposed strategy is more advantageous when building energy consumption is particularly high. In conclusion, the proposed strategy, even if applied to the Italian context, could be generalized to other countries with similar electricity tariffs and regulations to improve the sustainability of large commercial buildings. Further studies will be performed in future to verify whether the PEC strategy is able not only to shave peaks for economic reasons, but also to smooth load profiles to support grid services.

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