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RESEARCH ARTICLE

An Efficient Artificial Intelligence Energy Management System for Urban Building Integrating Photovoltaic and Storage

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ABSTRACT The emerging leading role of green energy in our society pushes the investigation of new economic and technological solutions. Green energies and smart communities increase efficiency with the use of digital solutions for the benefits of inhabitants and companies. The paper focuses on the development of a methodology for the energy management, combining photovoltaics and storage systems, considering as the main case study a multi-story building characterized by a high density of households, used to generate data which allow feasibility foresights. The physical model of the algorithm is composed by two main elements: the photovoltaics modules and the battery energy storage system. In addition, to gain information about the real-time consumption a machine learning module is included in our approach to generate predictions about the near future demand. The benefits provided by the method are evaluated with an economic analysis, which computes the return of the investment using the real consumptions of a Boarding School, located in Turin (Italy). The case study analyzed in this article showed an increase in purchased energy at the minimum price from 25% to 91% and a 55% reduction in the electricity bill compared to most solutions on the market, with no additional costs and a stabilizing effect on the grid. Finally, the economic analysis shows that the proposed method is a profitable investment, with a breakeven point of thirteen years, due to the very simple implementation and the zero additional cost requested.

INDEX TERMS Deep learning, energy management systems, energy storage, environmental economics, renewable energy sources.

I. INTRODUCTION

The emerging leading role of green energy in our society pushes the investigation of new economic and technological solutions. However, at higher-level RESs penetration, the systems become more complex to be controlled and balanced [1]. The actual political situation and environmental awareness are pushing toward the energy transition. In this context, for example, the European Commission (EC) has published the "EU Solar Energy Strategy" [2], trough which it aims to bring online over 320 GW of solar photovoltaic by 2025 (more than doubling compared to 2020) and almost 600 GW by 2030. Traditional photovoltaic (PV) plants, on the other hand, can only generate electricity during daylight hours. Because of the lack of nighttime performance, expensive batteries and grid connections to alternative energy sources, most notably fossil fuels, are required [3].

In this scenario, the possible installation of Renewable Energy Sources (RES) in urban context can have a key role in a feasible energy transition. Due to this reason, there has been

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a surge in interest in Building-Integrated Photovoltaic (BIPV) applications in urban structures during the last 10 years. Reference [4] emphasizes that just a few studies look at the integration of PVs with smart grids, particularly regarding BIPV systems. These are integrated into the structure and replace specific structural parts (roof, façade, etc.), whereas building-added PV systems are added to a structure. BI solar systems provide visually beautiful structures as well as the replacement of some building components. More in general, cities are undergoing a profound shift in terms of energy and sustainability, with increased density and a scattering of urban distribution: this phenomenon can represent an opportunity for energy management and distribution [5]. Even if the just past global Sars-CoV-2 pandemic has slowed this apparent urbanization tendency, we can expect a comeback as soon as the health crisis is over, without jeopardizing this human aggregation paradigm [6]. The development of modern residential units, whose main dimensional characteristic is based on their exponential height, was prompted by the increasing congestion of cities. The notion of energy communities was born out of the urban concentration of several homes in a single building, allowing resource and land use management to follow a low-emissions strategy [7].

Due to their intrinsic stochastic nature, RES can introduce instability in the electric network. Thus, a key element for obtaining a feasible energy transition is the capability to achieve a good forecasting of RES production and electric load [8]. Many works in the literature address the problem of either short-term [10] or long-term forecasting [9].

Around the world, energy communities are forming to raise awareness and reduce waste, based on creating a smart grid. This system allows users to trade energy while reducing prices and waste. The notion of an energy community is vital in urban government since it has direct implications for various environmental issues [31].

As concluded in [4], one of the key challenges for the evolution of the smart grids, integrated with PV systems, is in the opportunity to deal with the intermittent power generation through the smart data management. In this sense, prediction on the demand and the production could permit to attenuate the highlighted problems if this information would be properly use. Indeed, this paper investigate the opportunity coming from the store of electricity when the electrical demand to the grid is lower (typically the night), and to use it during the day, with the one produced by the PV system. In other words, the system would forecast the amount of energy used by the building's residents as well as the amount of energy produced by the PV system on the same roof. The difference represents the energy that should be purchased throughout the day: the program would acquire it at night, when it is normally cheaper, and store it in the building storage system for use the next day.

The aim of this work is to introduce a hybrid control strategy based on physical models of the system components and machine learning methods for the prediction of electrical load and RES production. This control strategy has been specifically designed for the management of loads in an urban context; in particular, the system should optimize the cost of electricity in condominiums where structural constraints limit the installable capacity of photovoltaic and battery energy storage (BESS) systems.

This control strategy will exploit both photovoltaic production and the time-of-use energy tariff in order to maximize the profits that can be obtained through the installation of energy storage systems.

This study brings several contributions to the field. Mainly, this research proposed a power flow algorithm that combines the exploitation of RES and time-of-use tariff to improve the economic advantage of using BESS. Indeed, the proposed algorithm can lead to a reduction of the final energy price perceived by the private users. Furthermore, the hybrid use of physical models and of machine learning, with the Temporal Convolution Neural Network, represents another significant novelty of this work.

Aside from the reduction in energy price, there are two other major advantages of the use of the proposed algorithm: it maximizes the use of RES and it leads to a higher installation of BESS that can be used to increase the electric network stability.

The remaining of the paper is structured as follows. Section II describes the State-of-the-Art of the research and of the industrial applications of integrated BESS system. Then, in Section III the proposed method is described, detailing both the physical and the data-driven models implemented. In Section IV the case study used to test the proposed method is described and in Section V the obtained results are shown. Finally, in Section VI some conclusions are drawn.

II. STATE OF THE ART

A. DEMAND FORECASTING

The problem of modeling and forecasting the electric load can be categorized as a time series prediction problem. It is characterized by a series of challenges that are due to the specific nature of the measures of interest: fluctuations due to random behavior of the users operating in the system of interest, and seasonal and weekly trends. The way in which these issues affect the overall load can vary at different scales. In the literature there are mainly two categories of approaches: traditional, statistical methods, and Machine Learning based ones. They are hereby discussed, and a summarization of them is present as well in Tab. 1 exemplyfiyng for each paper the used algorithms and metrics.

Statistical models like SARIMA model were used in [11]. Other traditional approaches based on multi-predictor regression were applied in [12] and [13] to study both hourly and daily energy consumption profile. Researchers also tried to boost the performance of simple ARIMA models by Bootstrap aggregating them in [14]. The main drawback of purely statistical method is their inability to well capture the highly non-linear behaviors that arise in consumption profiles. This effect is amplified at smaller scale; in fact with higher volumes considered, the random fluctuations tend to even out.

Moving on towards Machine Learning based methods, the first approaches that showed good results were based on Support Vector Regressors [15], [16] or ensemble learning techniques and Adaboost to forecast energy consumption [17]. Despite the improvement they provided, these method still failed to reliably complete the forecasting task, mainly due to overfitting, caused by evolving correlation over time among the data. The more modern approaches come from Deep Learning, as they try to exploit the elevated number of parameters to capture complex temporal dependencies. Simple ANNs are adopted in [26], whereas Cascaded ANNs are proposed by [29] for resource forecasting. Fuzzy systems (ANFIS) are also employed in [21] and [29].

Other works were based on more complex architectures such as Recurrent Neural Networks (RNN) like [18]. The main issue with RNN is that they struggle in keeping "memory" i.e. detect pattern on long temporal scales, like seasonal trends that are fundamental in consumption profiles. An improvement in this sense comes from Long-Short Term Memory networks (LSTMs), as they were applied in [19]. For many years the LSTMs have gained large popularity, as witnessed by the large body of research expanding on them. Indeed, they are also exploited in [25], where firstly a CNN is used to extract the embedding for the LSTM recurrent cells. Moreover, in [27] they embed the LSTM cell in a Non-Linear Auto-Regressive framework, in which the feedback loop of the regressor contains time-step delays. A complete comparison of traditional ML methods like Linear Regression and Support Vector Machines (SVMs) versus Multi Layer Perceptrons (MLPs) and LSTMs can be found in [26], applied to day-forward predictions in a context of microgrid clusters. Despite their success, LSTM-based architecture struggle when complex and multi-scale temporal dependencies are present, as shown in [28]. Subsequently, another kind of architecture that improves the capability of detecting long-range temporal dependencies was proposed, the Temporal Convolutional Network. This architecture was applied to the energy demand task in [20], but only at a national scale. An alternative approach is found in [24], where they employ a model similar to TCNs, but they tune the hyper-parameters via an evolutionary algorithm. Moreover, [21] analyzed the potential and issues of increasingly deep models specifically applied to the residential case.

More recently some more elaborate models have been proposed, like [22], that introduced an attention mechanism in order to detect upcoming and unforeseen surges of demand. Another modern architecture, that has recently been gaining popularity across different fields is the Transformer architecture, characterized by the mechanism of self-attention. The work of [23] shows the potential of these kind of models. Machine learning algorithms have been also adopted in order to forecast changes in energy consumer pattern, due to event as the past pandemic one, and to support the energy suppliers, grid operators, and traders to better calculate the required operational flexibility [30].

Overall, the analysis of the literature indicates that Deep Learning-based methods are getting increasingly accurate and robust, thanks to their capability of modeling complex and non-linear functions, with dependencies evolving overtime.

B. EXISTING SOLUTIONS FOR BUILDING ENERGY MANAGEMENT

Nowadays, the generation of electricity from renewable energy sources (RES) is becoming increasingly important to achieving the ambitious targets of reducing greenhouse emissions set in the 2015 Paris Agreement [32]. Thus, renewable energy generation such as solar or wind power generation is spreading worldwide, leading to the problems of their intrinsic variable nature, whose outputs could vary temporally on many scales, and their integration into the energy system [33]. In this context, governments and energy multiutilities are questioning themselves which could be the most fruitful model to adopt in order to solve these challenges. According to [34], it is evident how a viable solution is represented by the integration of photovoltaic panels and energy storage systems (ESS) into the buildings in a perspective of community-scale micro grids within a city. In fact, considering a bidirectional energy flow, where people may both buy and sell energy, smart grids ensure a high penetration of stochastic and intermittent renewable energy. Due to their variable nature, these grid systems are experiencing high voltage fluctuations leading to power quality problems that need to be controlled and stabilised in order to guarantee an ever-high quality service [35]. Therefore, in recent years there has been an increasing amount of work seeking solutions to stabilise these processes. In particular, [36] proposed and validated a new control scheme applied to a solar and wind hybrid power generation system (HPGS) linked to a power grid, introducing a supercapacitor to smooth out the ripple on the distribution side in the power grid. Instead, [37] adopted a deep learning model to predict the stability of a simulated smart grid. However, proper implementation of these technologies in a building environment can be obtained only with an appropriate energy management system, which controls the flow of energy between energy production (through PVs), energy consumption, and energy storage, optimizing costs through a link with the energy grid network [38], [39].

Thus, analysing the state of the art of the energy systems for PV and storage energy management, it can be noted that most of the software already present on the market are private tools, developed by multiutilities. As highlighted by [40], it is rare to find literature that analyses a local energy market in which prosumers and consumers can actively participate in the power supply process by exploiting ESS. Only a few examples of building energy management software can be found in the literature.

TABLE 1. State of the art papers comparison.

No	Reference	Method	Evaluation Metrics	Description
[11]	V. G. Tran et al.	ANFISS ARIMA	Weekly Mean Error (WME)	Compares two forecast models using electric load data from Vietnam's Hanoi city. These two models are Seasonal Auto Regressive Moving Average (SARIMA) and Adaptive Network Based Fuzzy Inference System (ANFIS). The results show that the SARIMA model is preferred in our scenario.
[14]	E. M. de Oliveira et al.	Bootstrap aggregation ARIMA	Mean Absolute Percentage Error (MAPE) Symmetric Mean Absolute Percentage Error (sMAPE) Root Mean Squared Error (RMSE) Theil Inequality Coefficient (TIC)	Employs a combination of decomposition and Bootstrap aggregating (Bagging) techniques to estimate for monthly energy consumption across many nations. A novel bagging technique is suggested here and given the name Remainder Sieve Bootstrap (RSB). Results confirm an increase in forecast accuracy.
[15]	R. K. Jain et al.	Support Vector Regression (SVR)	Coefficient of variation mean Coefficient of variation standard error	Support Vector Regression (SVR) is used to create a forecasting model, then applied to a data set from a multi-family residential building. Results demonstrate that multi-family residential buildings are best suited for forecasting models when the monitoring granularity occurs at the by-floor level in hourly intervals.
[16]	Y. Liu et al.	Support Vector Machine (SVM)	Average relative error Root mean square error (RMSE)	Based on historical consumption data, meteorological conditions, and time-cycle factors, this paper proposes a support vector machine (SVM) approach to predict public building energy consumption. The study period was defined as the months with airconditioning energy consumption in Wuhan.
[17]	T. Pinto et al.	Ensemble learning Gradient boosted regression trees Random forests Adaboost	Mean Absolute Percentage Error (MAPE)	This paper compares three ensemble learning models for short term load forecasting. These models are: gradient boosted regression trees, random forests and an adaptation of Adaboost. An hour-ahead consumption forecasting case study on data from an office building is used. They demonstrate that the modified Adaboost model performs better than reference models.
[18]	A. Rahman et al.	Recurrent Neural Networks (RNN)	Root Mean Squared Error(RMSE) Pearson Coefficient	This study provided a recurrent neural network model to develop one-hour resolution predictions of power consumption profiles in commercial and residential buildings When compared to the traditional multi-layered perceptron , the suggested RNN seq-to-seq models achieve lower errors in predicting the load profiles.
[20]	P. Lara-Benitez et al.	Temporal Convolutional Networks (TCN)	Weighted Absolute PercentageError (WAPE)	Proposes a TCN-based model to boost forecasting of energy demands predictive ability. The analyze national electric demand and the power demand at electric vehicle charging stations in Spain. Traditional LSTMs networks are outperformed by the TCN.
[21]	M. Fayaz et al.	Deep Extreme Learning Machine (DELM) Adaptive Neuro-Fuzzy Inference System (ANFIS) Artificial Neural Network (ANN)	Mean Absolute Error (MAE) Root Mean Squared Error (RMSE) Mean Absolute Percentage Error (MAPE)	A method for estimating energy consumption in residential structures was proposed. The suggested approach used four distinct layers that adopted DELM, ANFIS, and ANN. They gathered actual data from a four-story residential building for experimental research. According to the results, DELM performs significantly better than ANN and ANFIS.
[22]	Y. Gao et al.	Seq-To-Seq Convolutional Neural Network (CNN)	Mean Absolute Percentage Error (MAPE) Coefficient of Variation of RMSE (CV-RMSE)	This paper compares two deep learning models: a seq2seq model and a two-dimensional (2D) convolutional neural network (CNN). Three office buildings are used as a case study. Both models outperform an LSTM network.
[23]	L. Saad Soud et al.	Stationary Wavelet Transform (SWT)	Mean Squared Error (MSE) Root Mean Squared Error (RMSE) Mean Absolute Error (MAE) Mean absolute Percentage Error (MAPE)	This paper provides a household power consumption forecasting method, using models based on the stationary wavelet transform (SWT). Transformers are utilized to anticipate the SWT subbands. According to results, their hybrid approach outperforms other power consumption prediction techniques.
[24]	S. M. J. Jalali et al.	Convolutional Neural Networks (CNN) Enhanced Grey Wolf Optimizer (EGWO)	Root Mean Squared Error (RMSE) Mean Absolute Error (MAE) Mean absolute Percentage Error (MAPE)	Novel approach to the electricity load forecasting based on an Australian dataset. It is focused on predicting medium-range load with an overall perception regarding power systems and electricity markets.
[25]	S. H. Rafi et al.	Cconvolutional Neural Network (CNN) Long Short-Term Memory (LSTM) network	Mean Average Error (MAE) Root Mean Squared Error (RMSE) Mean Absolute Percentage Error (MAPE)	This study tackles short-term electrical load prediction. The method integrates CNNs and LSTMs. The dataset employed contains data from Bangladesh power system. LSTMs, radial-basis function network and gradient boosting are compared.
[26]	S. N. V. B. Rao et al.	Linear Regression (LR) Support Vector Machine (SVM) Long short-term memory (LSTM) Artificial Neural Network (ANN)	Root Mean Squared Error (RMSE) Mean Squared Error (MSE) Mean Absolute Error (MAE) Mean absolute Percentage Error (MAPE)	Load forecasting issue in urban community cluster microgrids is investigated. In particular, the Linear Regression (LR), Support Vector Machine (SVM), Long Short-Term Memory (LSTM), and Artificial Neural Network machine learning techniques are used (ANN). In addition, three optimization methods are employed. Results show that the Levenberg-Marquardt optimizer paired with ANN is the best choice.
[27]	M. Massaoudi et al.	Nonlinear Auto-Regressive Neural Network (NARXNN) Long Short-Term Memory (LSTM)	Root Mean Squared Error (RMSE) Mean Squared Error (MSE) Average Coverage Error (ACE) Predict. Interval Normalized Avg Width (PINAW) Predict. Interval Nominal Confidence (PINC)	An architecture based on the combination of Long Short-Term Memory (LSTM) and Nonlinear Auto-Regressive Exogenous Neural Network (NARXNN) was developed for PV power forecasting.
[29]	M. Amir et al.	Adapt. Neuro Fuzzy Inf. Sys. (ANFIS) Cascaded ANNs	Mean Squared Error (MSE) Mean absolute Percentage Error (MAPE) R^2	System made up by(i) a mixed input cascaded ANN (CANN) is realized for prediction of a short-term solar irradiance and wind speed and (ii) ANFIS model is simulated for short-term power demand prediction. The approach is tested on a historical hourly dataset.
[30]	S. V. Oprea et al.	Long Short-Term Memory (LSTM) Regression Analysis (RA)	Root Mean Squared Error (RMSE) Mean Squared Error (MSE) Mean Absolute Error (MAE) Mean absolute Percentage Error (MAPE)	This paper applies a cloud-based processing method to commercial buildings. It offers a novel approach to evaluate the load flexibility of commercial structures and determine its advantages. An hourly dataset from the U.S.A. values with electricity and gas consumptions over a year is used. They compared LSTMs and RA, obtaining results close to the actual consumption values.

In particular, the most of research studies applied in this field are related to peer-to-peer energy trading in the context of future energy communities. According to [41] and [42], energy communities have developed as new entities that not only provide end-users with unique platforms for investing in low-carbon assets but also as operational market entities capable of exchanging energy excess (deficit) among their peers. In fact [43] investigates the benefits of a three-layered architecture comprising cloud, fog, and consumer layers in a smart grid environment. It highlights how the application of this architecture allows an optimization of the resources, minimizing the system's response time and processing time. Whereas [44] and [45] analyse the advantages and disadvantages of an optimization model to schedule peer-to-peer transactions via the local electricity market, grid transactions in the retail market, and battery management. They consider the photovoltaic production of households in local energy communities, showing that combining the use of peer-to-peer transactions and energy storage systems can potentially provide consistent energy savings in the future. Similar results are obtained by [46] through its study on the problem of a smart community, composed of a group of grid-connected prosumers with controllable loads, renewable generations, and energy storage systems. It demonstrates that the energy exchange in the proposed scalable energy trading system results in considerable increases in energy cost reductions and renewable energy usage efficiency. However, all this research relates to the future development of energy communities, while there is a clear lack of solutions that can be implemented in a city context today. The analysis provided in [61] show some preliminary results on a day-basis time frame, where the BESS is used for both RES integration and exploitation of different tariffs. These results provided a first economic analysis, but it is important to increase the time resolution of the forecasting and optimization models to be able to consider the power flow, and, possibly, new features such as the possibility to provide grid services.

Nevertheless, one possible solution is provided by [47] that developed an algorithm to manage a building energy storage system (BESS) to reduce the electricity price and the peak

TABLE 2. State of the art software comparison.

	Tesla Autobidder Tesla Opticaster	Tesla Powerhub Tesla Microgrid Controller SMA Power Plant Manager	Enel X DER Optimizator	Sonnen LG Chem CellCube Samsung SDI
Integration into buildings			●	●
Predictive capability	●			
Independent energy management	●	●	●	
Speak to users	●	●	●	

load acting on the charge and discharge phase of the BESS, by predicting the monthly load data of the building. Their results highlighted how the electricity price was minimized by peak load and electricity usage reduction. However, this system was based only on the building energy data without considering the forecasting of possible renewable energy production. This lack of forecasting capability is a common property of lots of the commercial PV and storage management software, developed to manage these technologies in the facility environments. These software can be identified in: Enel X's DER Optimization Software [48], SMA's Power Plant Manager [49], Homer [50], Energy Toolbase [51]. Hence, the forecasting capability is present only in Tesla's solutions like Opticaster or Autobidder [52], which are however not directly feasible in a city building context. In this environment, in fact, there are currently only photovoltaic panel and storage system solutions such as those of Sonnen, Tesla Energy, LG Chem and CellCube, which are not equipped with an energy management, prediction and optimization software, but only with the hardware and a storage control unit.

In order to summarize and compare all these considerations and assess whether or not there is a gap in the current energy market, it was decided to make a comparison using the following four drivers:

1) *integration into buildings*: the capability of a solution to be easily inserted into a smart building context; perform prediction analysis to make appropriate choices in energy management between storage systems, PV and the grid;
2) *predictive capability*: perform prediction analysis to make appropriate choices in energy management between storage systems, PV and the grid;
3) *independent energy management*: the ability of a solution to manage energy flow autonomously;
4) *speak to users*: the capacity of a solution to interact with users and make them aware of the actions and functioning of the solution itself.

Taking into account these drivers, the comparison analysis shown in Tab. 2 was obtained.

Hence it can be seen in Tab. 2, that there are no solutions at the state of the art that contains all the strong points that we identified as drivers of a successful solution, capable of covering the aforementioned challenges of the energy market. This analysis, indeed, was the starting point for the development of our whole project, which has in these characteristics its strength and its novelty: we aim to develop a software that offers a solution for city buildings to predict and optimize the energy flow among PV production, building consumption and energy bought from the grid.

III. METHODS

A. PROPOSED METHOD

The proposed method plugs itself in a scenario that essentially comprehends a building equipped with a PV and a storage system. The overall system is depicted in Fig.1, which is split in 2: above, the training scheme for the AI module that predicts energy demand (discussed below). In the bottom part of the figure, all the inputs to our system are exemplified, as well as the relationship between modules in our overall architecture, and how they interact with the building. Individual modules are described in the remaining parts of this Section.

The system has 2 main sources of inputs: one coming from the building, where the software has to monitor the state of the storage, and receive live-data about the energy demand.

Another important input comes from the weather forecast, that is going to be applied to the physical model of the PV to extrapolate the forecasted power output. The information about the real-time consumption is used by the AI module to generate predictions about the near future demand. The solar irradiance forecast gathered from the web is instead processed by the physical model component to compute the power output of the PV.

Internally, these pieces of information are combined, and then fed to the optimizer module that provides the strategy to follow. The strategy in detail consists in deciding at what time and what amount of energy has to be purchased from the grid, with the goal of fully exploiting the storage asset and maximize final energy self-consumption while reducing the overall cost for the user. The strategy can also be updated after each new weather forecast or overridden by the building manager to deal with sudden severe weather events.

B. PHOTOVOLTAIC MODULES PHYSICAL MODEL

In order to buy the proper amount of energy during the night, it is of paramount importance that the algorithm can accurately predict the power produced by PVs. During the last years many physical models have been developed in order to forecast the power production of photovoltaic modules based on weather forecasts [53]. The most common and accurate model of PV cell is an equivalent electric circuit based on three, five or seven parameters. Results in [53] show that there is no clear advantage in using the five or seven parameters

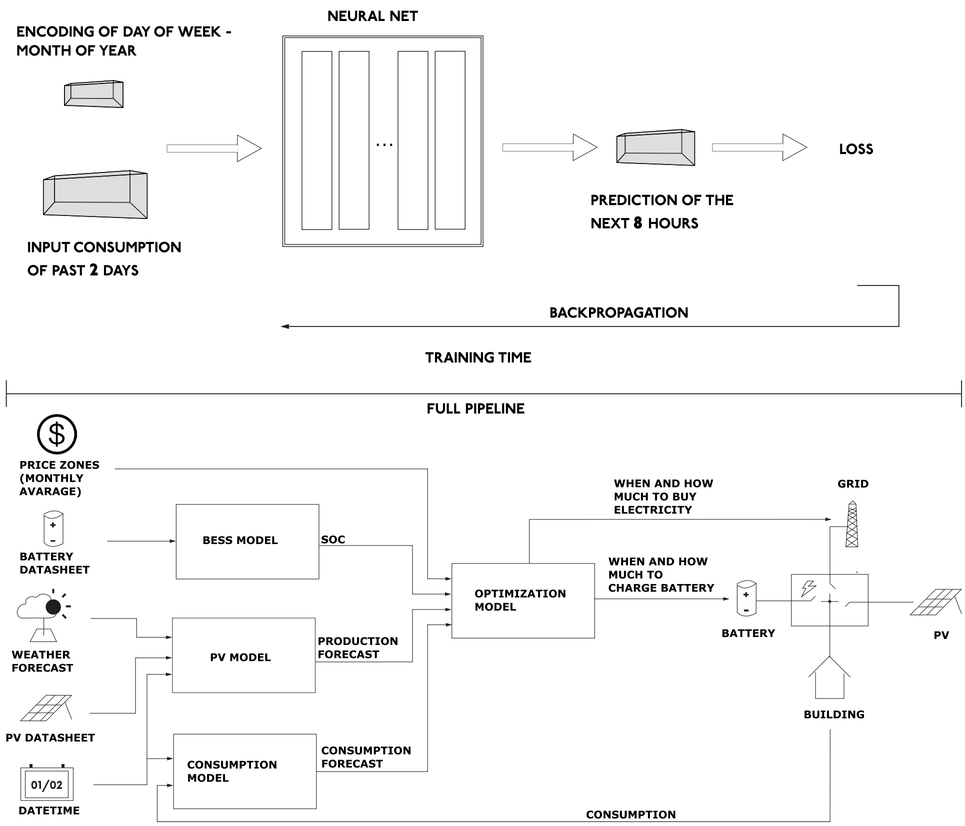

FIGURE 1. Architectural block diagram of the proposed solution. In the above picture, the training procedure of the AI-based consumption predictor block is schematized. Below, the flow of information through the whole pipeline is clarified: the physical models provide the Optimization block with information about the SOC and forecasted energy production, whereas the consumption predictor outputs demand forecast. These pieces of information are processed by the Optimizer which in turn acts on the building to maximize the energy quota bought at minimum price.

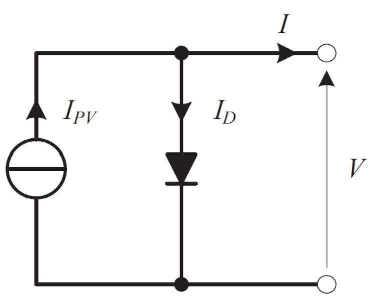

FIGURE 2. Equivalent circuit representing the three-parameter model adopted.

instead of three one. Hence, we decided to model the PV cell as the three parameter circuit shown in Figure 2 that includes a current generator and a diode connected in parallel that is described by the following equation:

$$I = I_{PV} - I_0 \left(e^{\frac{V}{n_s V_t}} - 1 \right) \tag{1}$$

where I_{PV} is the photocurrent, I_0 is the dark saturation current, n_s is the number of series connected cells in the module and V_t is the module thermal voltage.

The obtained model allows to predict the power produced having as input:

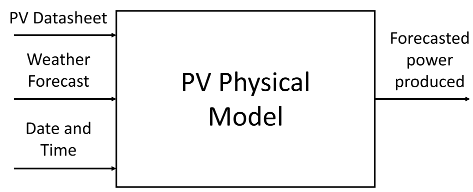

FIGURE 3. Graphic representation of the PV model.

- the PV datasheet,
- the weather forecast: the diffuse irradiance (G_{DIFF}), the direct normal one (G_{DNI}) and the ambient temperature (T_{amb}),
- the date and time (to evaluate the relative position between the PVs and the sun).

A graphical representation of the model is shown in Figure 3. The performance of a PV cell is strictly related to its temperature (T_C). A good approximation is given by the Nominal Operating Cell Temperature (NOCT) equation:

$$T_C = T_{amb} + \frac{NOCT - T_{amb@NOCT}}{G_{NOCT}} \cdot G_{TOT} \tag{2}$$

By using this formula, the cell temperature is obtained assuming that the difference between ambient temperature and the PV one is proportional to the total irradiance (G_{TOT})

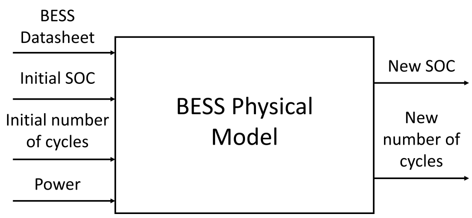

FIGURE 4. Graphic representation of the BESS model.

starting from a reference condition: $NOCT = 50°C$, $T_{amb@NOCT} = 20°C$ and $G_{NOCT} = 800\ W/m^2$.

Finally, the model was implemented using the Solcast™ environment tools [54] with irradiance and temperature data as input for plant power forecasting.

C. BATTERY ENERGY STORAGE SYSTEM PHYSICAL MODEL

We modeled also the battery energy storage system (BESS) using [55] as main reference.

In particular, we wrote the efficiency of the BESS for its cycle of charge and discharge as a function of its state of charge (SOC), its number of life cycles [56] and the power used as input (Figure 4).

Note that data provided by the two papers want to be just a support for the model-building, but they cannot be applied at any storage. Indeed, the characteristic values of the actual installed storage must be provided by datasheets or measured.

Considering a flux of power P associated to the storage (positive if it charges the BESS, negative otherwise), the relative energy value can be calculated by integrating P over time:

$$E_n = \int_{dis/char} P(t) \cdot dt \tag{3}$$

and, during this process, the SOC changes as

$$\begin{cases} SOC(t=0) = SOC_{init} \\ SOC(t>0) = SOC_{old} + \dfrac{E_n}{E_{max}} \end{cases} \tag{4}$$

where SOC_{init} represents the initial state of the BESS, SOC_{old} is the SOC before the new operation and E_{max} is the maximum capacity.

The model proposed, before changing the state of charge, verify that:

- *In case of positive power,* that the battery capacity can admit the charging load. The storage admit energy up to saturation.
- *In case of negative power,* that the SOC is not null.
- *In any case (discharge and charge),* that the power flux does not overcome the maximum power, whose value is provided by data sheet.

The efficiency of the BESS is taken into account as follow:

$$P_{actual,discharge} = \frac{P_{discharge}}{\eta} \tag{5}$$

where η is the efficiency of the BESS considering both the effect of the SOC and the number of cycles. In particular, to avoid excessive underestimation of the system performance, this correction is done only in the discharge phase. Because the data of this model are extremely problem dependent, the final algorithm will start using these data and it will be trained continuously with real data measured, in order to correct itself automatically.

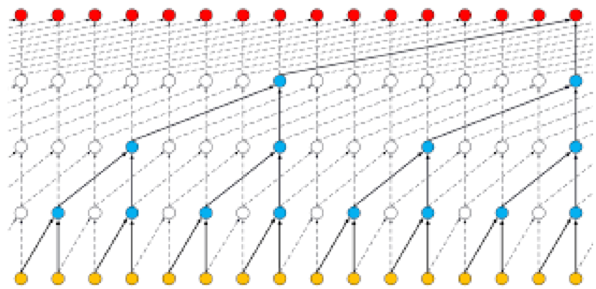

FIGURE 5. High level representation of a TCN.

D. AI MODULE: ENERGY DEMAND PREDICTION

This section presents the proposed framework with an AI module trained on an energy consumption dataset. Within such framework, at inference time (i.e. when the trained model is being used by the system with live data) the output of the model is used jointly with the physical models of PV and storage and the irradiance forecast from the Solcast API to optimize the self-consumption of the final user, minimizing the overall energy purchase while maximizing, among the necessary purchases, the energy quota bought at the lower price range.

The considered problem of energy forecasting has many factors of variability that have to be captured by a model that has to explain the data. Besides the amount of energy that can be considered as *baseload*, that is constituted by always-on appliances and recurrent habits (e.g. refrigerators, night lights), there are both *seasonal*, *weekly* and *daily* trends. Moreover, demand peaks are also frequent due to random use of energy hungry appliances. Therefore the model of choice will require a high capacity, in order to be able to quickly respond to the peaks and learn the different time-scaled trends. This means that for example a simple or multiple regression will not be sufficient; and a more powerful model is required.

In this work we propose the use of Temporal Convolutional Networks, as discussed in Sec. I, also adopted in [20]. The basic block of a TCN is depicted in Fig. 5, showing the causal dilated convolution and how the depth allows upper-level layers to have a broad receptive field. The formulation for a dilated causal convolution over sequential layer is as follows:

$$x_l^t = g(\sum_{k=0}^{K-1} \omega_l^k \cdot x_{l-1}^{t-(kxd)} + b_l) \tag{6}$$

In this formalism x_l^t is the output of the neuron at position t in the $l-th$ layer; K represents the convolutional kernel size; ω_l^k stands for the weight at position k, whereas d is the

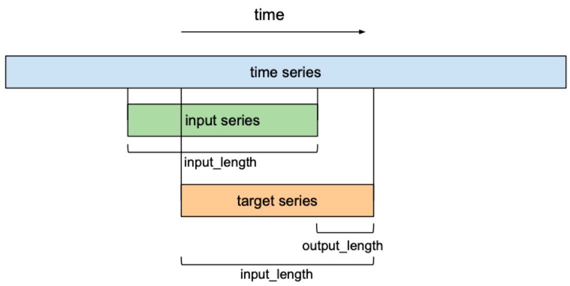

FIGURE 6. Representation of the operative way of using the model.

dilation factor and b_l. The function g is the activation function of choice which in modern DL in convolutional layers is traditionally the Rectified Linear Unit.

1) TRAINING PROCEDURE

This paragraph describes the training procedure of the consumption predictor block in our system. It is tasked with predicting the demand, based on the inputs of the recent past consumption, day and month. We describe operatively the devised framework for training and inference with the developed model. Mainly this means discussing the preprocessing of the dataset, choice of a training loss, and inference scheme.

The adopted dataset is a private collection of data from 1047 houses monitored for 2 years with data points every 15 minutes. The data was normalized with a min-max normalization scheme.

Another point to discuss is how many houses to group together to predict their total demand. This is mainly a trade-of between the cost of the storage, which is of course higher as you have higher demand, and the availability of data; since grouping together a high number of samples drastically reduces the final number of samples actually available for training. The final choice turned out to be 20.

As for the inference scheme (i.e. prediction horizon), this was mainly an issue of performances; the further you try to predict in the future, the less performant it will be; whereas the further you look back in the past the better, but having huge sequences yields also a heavier model and more difficult training. After some experiments the final model uses data about the previous 2 days, outputting predictions for 8 hours in the future. The model is used in a sliding window fashion, as depicted in Fig. 6.

Regarding the choice of the optimizer, in the field of Deep Learning SGD-based algorithms (Stochastic Gradient Descent) have become the de-facto standard. In the energy community they are fairly popular, adopted by [20], [21], [22], and [28]; however there are works that exploit other algorithms such as Levenberg–Marquardt in [26] and [29]. We chose to rely on SGD given its efficient implementations available in the PyTorch framework, and among its existing variants (SGD, Adam, AdamW, LARS..) we selected SGD by experimental validation.

TABLE 3. Monthly averages over the years 2015-2019 for each price bands in Italy.

	F1 [€/MWh]	F2 [€/MWh]	F3 [€/MWh]
Jan	75.96	69.17	58.51
Feb	59.19	56.61	48.26
Mar	55.28	47.38	47.95
Apr	56.66	49.40	43.61
May	52.36	51.34	43.82
Jun	52.93	42.12	35.28
Jul	56.63	49.28	40.92
Aug	47.87	43.07	38.12
Sep	55.10	46.90	42.67
Oct	59.40	49.16	40.43
Nov	57.08	49.79	39.30
Dec	50.43	44.96	33.98

The network has been trained for 30 epochs with a Stochastic Gradient Descent optimizer and a Learning Rate of 10^{-3}. The loss used was the **Mean Squared Error** (MSE), suited to penalize errors when a quantity is the objective of prediction. Therefore, from a statistical standpoint the model estimates a Gaussian distribution conditioned on the input sequence, which is a very common setting for Regression tasks in which a real quantity is the objective.

As an additional form of regularization, the weight decay technique has been used. It consists in adding a term to the loss that penalizes the L2-norm of the network's weights. While this may seem odd, it is a very simple yet powerful technique whose effect is the one of a statistical regularizer; meaning it limits the capacity of the model in order to obtain an estimator with a lower variance. Put in practical terms, it avoids overfitting by asking that the weights be all close to zeros; this will encourage the network to increase the value of a weight only if it encodes useful information that actually minimizes the loss of interest (MSE in our case).

Therefore the final objective of the training optimization is reported below:

$$L(y, \hat{y}) = \frac{K_{MSE}}{N} \sum_{i=0}^{N} (y - \hat{y}_i)^2 + K_{WD} * \sum_{w_i=0}^{w_M} ||W_{w_i}||^2 \quad (7)$$

E. OPTIMIZING SELF-CONSUMPTION

This paragraph describes the devised algorithm that combines the outputs of the demand forecasting model and the physical models in order to predict demand, consumption, and act on the system in order to optimize the use of energy. Regarding the energy price, we referred to the Italian system of energy pricing, which shares many similarities with countries in Europe and across the world. It divides the day into 3 price bands, each with its price. The price, as it is common, is lower in off-peak time bands, therefore during the night. In our experiments, we used as price values the monthly average of prices for each slot in the last 5 years. In Tab. 3 details on the prices used can be found.

Regarding the choice of the timing of when to load the storage, it is mainly a trade-off between the consumption prediction horizon of the AI model, and the time required to physically charge the storage, since we want to be able to buy energy before the more costly price band kicks in. Due to the fact that our demand prediction window is of 8 hours, the choice has been for the algorithm to operate on the basis of 8-hours slots. Therefore, considering the nominal power of the storage in our test-case (detailed in Sec. V-B), in order to have enough time to load the storage during the lowest price band, the first decision for the day is taken starting at 5 am, relying on the prediction for the subsequent 8 hours and so until 1 pm.

Considering that we want to account for as much of the consumption of the day as possible, we add to the prediction of the model a simple heuristic to account for the rest of the day after 1 pm. The heuristic is the following: we take the history about the past month, compute the sum of energy deltas for the time slot of interest (1 am - 11 pm), and take the daily average over them. This simple yet powerful ideas has 2 advantages: has a bound with the period of the year at hand (accounting for seasonal trends), and is able to smooth out the effect of day-level outliers. The decision output is how much energy to be bought and loaded into the storage, according to the following formulation:

$$GAP_{i,j} = \sum_{i=0}^{j} E^{i}_{cons} - E^{i}_{prod} \tag{8}$$

$$\begin{aligned} E^{i,j}_{buy} &= GAP_{i,j} + EST\_GAP_{1am-11\,pm} \\ &\quad + -E_{storage} + MIN\_THRESH \end{aligned} \tag{9}$$

where the index i running in $0..j$ represents the current time slot. $GAP_{i,j}$ is the sum of the energy deltas that occur in the mentioned slot, computed subtracting from the predicted demand $Econs$ the forecasted energy produced E_{prod}.

$EST\_GAP_{1am-11\,pm}$ is computed with the heuristic described in the previous paragraph, and its purpose is to account for the energy deltas that occur in the rest of the day that is beyond the predictive model horizon.

The term $E_{storage}$ is needed to take into account the current state of the storage; so, if the stored energy already covers the predicted delta for the morning plus the estimated one for the afternoon, no energy will be bought. The last term, MIN_THRESH, is present as a kind of safety measure to avoid wearing out the storage; in fact it is recommended to increase the expected life at the rated efficiency of the storage, to not discharge it completely. It can be seen as a safety net to avoid discharging completely the battery and account for unforeseen demand peaks. In our experiments it has been set to 10% of the storage capacity.

Below is reported the pseudo-code that encodes the principles explained; it does not take into account the time required to load the storage (as the original code does) nor does it track events, and the main purpose of this code is to exemplify in an algorithmic fashion the concepts enounced. The complete script that makes use of our software package to run the optimizer routine can be found in our Github repository.

```
for day in year:
  for slot in slots:
    e_cons = demand_predict(model_cons)
    e_prod = \
      production_forecast(model_prod)
    gap = run_heuristic()

    if slot.price == min_price:
      e_to_buy = sum(e_cons-e_prod) +
        + gap - e_available +
        + min_thresh
      storage.charge(e_to_buy)
    else:
      try:
        self_consume
      except storage empty:
        buy energy
```

FIGURE 7. Pseudo-code of our optimization algorithm.

TABLE 4. Case study specifications.

Number of floors	6
Roof Surface	1500 m^2
Roof surface available for PVs	750 m^2
Number of apartments	183

Note that the decision on how much to load the storage is only considered during the F3 price band (the cheapest, nightly), and never, say, during F2. So during the night an estimate of the consumption of the following day is computed, and a purchase is made accordingly. The reason for this is the following: the F2 slot is valid from 7 am to 8 am and from 7 pm - 11pm. Given this hourly division, it is ineffective to consider doing any computation to buy in this slot. Indeed, if after 7 pm the storage happens to be empty because consumption exceeded foreseen demand, energy will be bought at this price anyway. Regarding the mere 1 hour between 7-8 am, at that time the prediction has just been computed and there are no sufficient further information.

IV. CASE STUDY

A key aspect of the project is represented by the understanding of the economic advantage that our solution can provide in the building energy management market. Therefore, it was decided to consider a specific case study, in which evaluating if an energy optimization management software could offer an effective benefit in terms of cost savings on the bill.

A. BOARDING SCHOOL ENERGY CONSUMPTION DATA

The Italian Boarding School "Collegio Universitario Renato Einaudi Torino 1935," which main characteristics are reported in Tab. 4 [57], was chosen as the reference building to perform our economic analysis.

The starting point of this analysis was to obtain the energy consumption data for our case study, reported in Tab. 5, from [61]. In particular, these energy consumption data are divided into three price ranges: F1, F2, and F3. In Italy, indeed, the energy price fluctuates, depending on the market, leading to

TABLE 5. Case study monthly consumption data - 2019.

	A1 [kWh]	A2 [kWh]	A3 [kWh]	TOT [kWh]
Jan	12676	10269	11149	34094
Feb	12351	10514	10999	33864
Mar	10900	10566	10839	32305
Apr	9722	859	10188	20769
May	9723	858	10188	20769
Jun	9813	9125	10618	29556
Jul	9786	8326	10061	28173
Aug	1902	1552	2588	6042
Sep	6205	5254	6916	18375
Oct	10346	9117	9543	29006
Nov	10677	10363	11318	32358
Dec	8959	7450	10516	26925
TOT	113060	84253	114923	312236

daily variations, depending on the request. According to the Gestore dei Servizi s.p.a. report [58], the energy price ranges in 2019 were divided as reported in the following:

- F1 range constitutes the most expensive one, covering most of the daytime from 8.00 to 19.00 from Monday to Friday;
- F2 is middle range, from 7.00 to 8.00 and from 19.00 to 22.00 from Monday to Friday and also from 7.00 to 22.00 on Saturday;
- F3 determines the hours in which the price decreases, from 23.00 to 7.00 from Monday to Saturday and from 0.00 to 24.00 on Sunday.

The Boarding School energy consumption data provides a monthly trend, while hourly subdivided values are required in order to assess the profitability of the solution. Indeed, comparing the hourly energy consumption data of the Collegio with the values of solar panel production, it is possible to evaluate how the delta of energy between consumption and production changes during the year. This delta of energy, indeed, is equivalent to the energy that needs to be bought at the minimum price day by day during the year. This kind of analysis will also make possible to achieve a first storage sizing, which will be necessary for the investment assessment that will be explained in the next section. Therefore, it was decided to scale these monthly values on an hourly energy consumption profile found in the literature.

B. DATA ANALYSIS

Due to privacy matters determine a lack of information in Italy regarding energy consumption, it was decided to use an hourly consumption profile, obtained from the London Datastore [59], coming from research undergone by the Acorn Energy Group using SmartMeter technologies. Acorn Energy [60], that is a conglomerate investing in electricity generation and security, observed a sample of 5,567 London households between November 2011 and February 2014 which have been monitored in their energy consumptions, taking readings every half hour. From this dataset it was possible to access data for the period from 16th October 2012 at 00:30 to 16th October 2013 at 00:00. Since energy consumption data are available for each half-hour, this allows an amount of 17520 values.

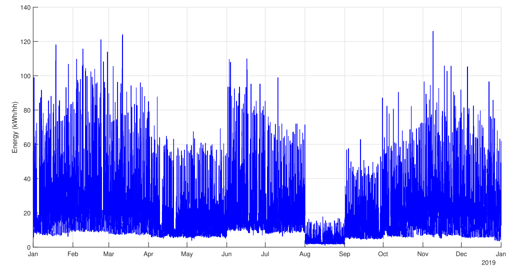

FIGURE 8. "Collegio Einaudi" annual energy consumption profile.

C. "Collegio ENAUDI" HOURLY ENERGY CONSUMPTION EVALUATION

Once the literature energy consumption profile was validated, the Collegio Einaudi's data were manipulated and scaled on the basis of the London values. Thus, an hourly distribution of energy consumption for the Boarding School was obtained from an overlay of both data:

1) the London households profile data was reordered to have a trend starting on 1 January at 00:30 and ending on 31 December at 00:00;
2) for each *i-th* consumption value (with $i = 1 : 17520$), its percentage weight on the total monthly consumption ($\%\ Monthly\ cons(i)$) was calculated through the following expression:

$$\%\ Monthly\ cons(i) = \frac{Hourly\ cons(i)}{\sum_{j=1}^{Nday} Hourly\ cons(j)} \tag{10}$$

where $Hourly\ cons(i)$ is the *i-th* value of energy consumption given by the reference dataset and *Nday* is the number of days per month;
3) these monthly percentage values were multiplied by the corresponding monthly consumption data of the Boarding School, already shown in Tab. 5. During this passage, a special attention was given to multiply the correct punctual percentage value to the respective monthly Boarding School one, taking into account the hourly energy price range division (F1, F2 and F3) previously described;
4) the next step consisted in omitting some out-of-scale values, replacing them with the average between the previous and the following one;
5) then, the week in which the UK household went on holiday (from 24 June 2019 at 00:30 to 1 July 2019 at 00:00), therefore not matching the Boarding School trend, was replaced with the consumption profile of the previous week;

The results are shown in Fig. 8. It is possible to observe a considerable discontinuity of data in August caused, obviously, by the very low consumption of the college linked to the students' summer vacations.

The next step was to assess a first estimation of the storage system sizing, exploiting the previously introduced PV model. In fact, following the procedure described in [61], it was possible to estimate the PV energy production profile of the Boarding School in 2019. Therefore, knowing the delta of energy between consumption and PV production for each day of the 2019, it was possible to assess a first storage sizing of $\simeq$1500 kWh.

V. RESULTS

A. INVESTMENT ANALYSIS

To evaluate whether the investment related to our solution could be viable or not, we decided to perform an economic analysis based on one of the well-known and most effective indicators in the PV and BESS energy system market: the Net Present Value (NPV). This metric indicates the difference between the present value of cash inflows and the current value of cash outflows under a period of time [62], [63], [64]. Moreover, further consideration of our analysis is based on [65], showing that tax deductions reduced the payback period for the investment and increased the annual savings from the energy storage systems.

As reported in the article [61], the break even time for the case study considered in the section IV is 13 years. This number was obtained by discounting the cash flows using the NPV considering the initial investment for the purchase of photovoltaic modules and BESS, the utility bill savings possible from the proposed solution, and the annual maintenance costs of the PVs. The main reason why the investment is paid back after so many years is the high initial cost associated with PVs and BESS. However, both the prices of PVs and BESS will decrease in the next years. Indeed, PV have exhibited the most rapid cost decrease among energy technologies, economy of scale being one of the main factor to comport this decrease and their economic potential lies in the further reduction of price expected in the next decades. US investment bank Lazard's edition of its annual Levelized Cost of Energy Report 2020 showed a 7% decrease on a year basis, expecting to reach values lower than for any other power source [66]. Considering the BESS, according to Bloomberg New Energy Finance New Energy Outlook (BNEF 2018) [67], over 1,200 GW of additional Li-ion battery capacity (a choice motivated by their high specific energy) is expected to be deployed by the year 2050. Investments over the next few years are expected to be located mainly in Asia and Europe reaching a combined total cost of \$544 billion (BNEF 2018). Between 2010 and 2017, battery prices have fallen by 80 percent, getting to an average of \$200/kWh, projections estimating that the price will reach approximately [68].

The combined use of photovoltaics and energy storage systems set the opportunity to generate a profitable investment characterized by increasingly growing profit margins. Hence, considering both PVs and BESSs prices reduction, we decided to analyze different scenarios in which such an investment made in different years would be evaluated. Furthermore, as can be seen from the following analysis, the implementation of our solution was not considered in the initial investment. This is because it is a zero-cost solution which can be perfectly and easily integrated into any hardware system that a company has already developed. The main components figuring in the initial investment costs are [61]:

- The PV plant: 129, 600 €
- Li-ion batteries: 570, 000 €

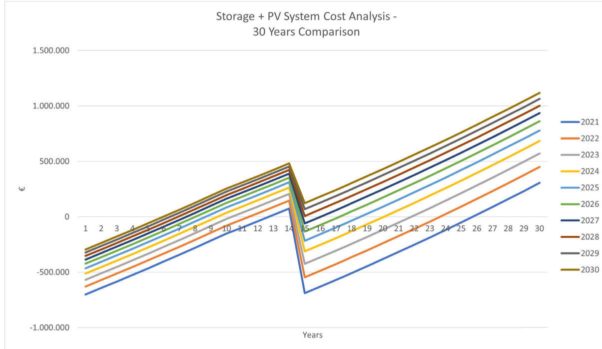

FIGURE 9. Cash flow analysis - investment comparison.

We projected the PV price by using the 7% decrease on a year basis [66] and the BESS price by applying the current mark-up to the projected price of the raw materials expected by Bloomberg (BNEF 2018). We considered also an average market cost of 35 €/kW of PV maintenance annual cost.

Hence, we evaluated different scenarios which differ for the considered moment of installation: the cost projections have been proposed varying the starting year from 2021 to 2030 and each investment scenario is evaluated for the following 30 years period (chosing, according to literature, a discount rate of 5% [69] for the NPV). We evaluated different scenarios which differ for the considered moment of installation: the cost projections have been proposed varying the starting year from 2021 to 2030 and each investment scenario is evaluated for the following 30 years period. Results are shown in Figure 9.

Final considerations show how NPV of the investment only becomes positive during the last year, the necessity to repay the expenses for the storage every fifteen years playing a relevant role on the profit margin. Meanwhile the cash flow of the project as seen in Fig.9 underlines how the profitability margin is steadily increasing over the years. Considering the batteries and PV trends in the future is acceptable to say the project investment is going to increase its profitability exponentially in a horizon of thirty years.

B. OPTIMIZED SOLUTION RESULTS

In this section are discussed the results obtained by applying the full proposed framework on the case study described in Section IV and comparing the results of a PV + storage system that implements the proposed solution, and a standard one that does not.

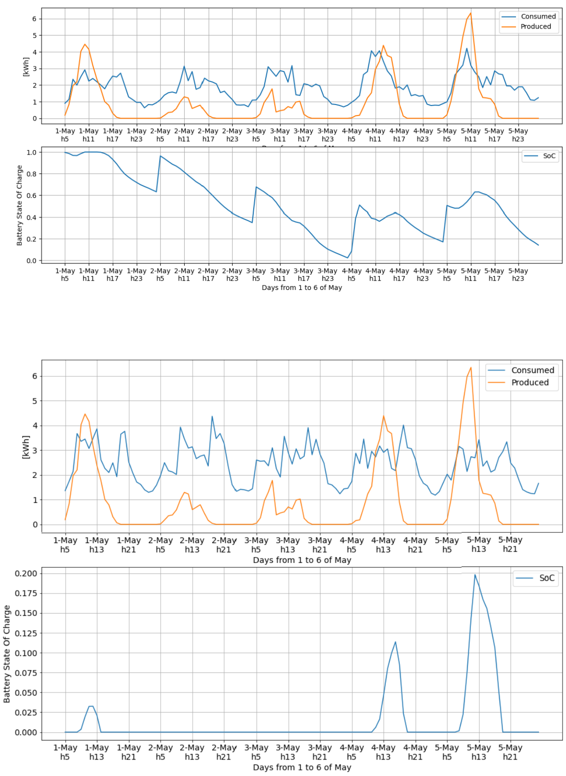

FIGURE 10. Results applying the ULISSE sofware: (a) behavior of the storage in a ULISSE system in response to consumption/production curves (b) behavior of the storage in a standard system in response to consumption/production curves.

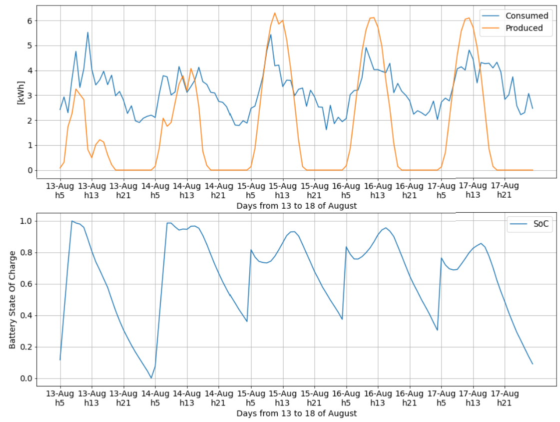

FIGURE 11. Results applying the ULISSE software in a situation of over-production in the month of August.

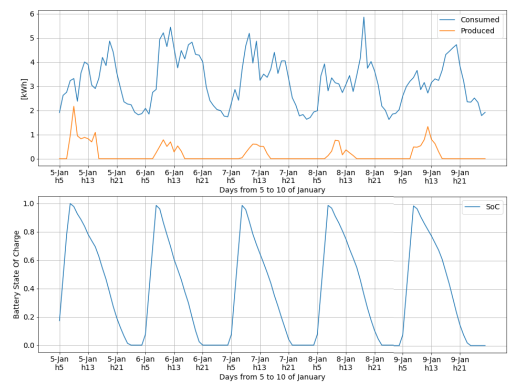

FIGURE 12. Results applying the ULISSE software in a situation of under-production in the month of January.

The analysis begins by looking at the curves reported in Figure 10, regarding the behavior of the system across 5 days in the month of May having some days below consumption, same days slightly above.

Specifically, Figure 10b shows what would be the state of the storage in the depicted days. Even though including a storage system is definitely a choice that will be more and more convenient in the future and it avoids to waste the excess of production, this curves show clearly how it can happen, quite frequently, that production cannot keep up with the demand, causing the storage to be unused.

Considering Figure 10a, which shows the behavior of the system during the same days, on a system that includes the proposed solution. These curves are quite explicative of the goal of the proposed system and also of the quality of results that it is able to provide. In particular, it can be noted how, for the days of May the 2nd and 3rd respectively, in which production rates were quite low, how our optimizer successfully applied the predictive model and the heuristics to decide to buy an extra quota of energy in the night shift, were all the charging spikes in the SOC are present. It can be seen how the system was able to reach the next charging slot without running out of energy and thus without having to pay for energy in the more costly bands.

For the second part of analysis results we will consider days in which production is consistently higher than demand, and viceversa.

Figure 11 depicts the situation, in the month of August, where the production can consistently, for more consecutive days, overcome demands. To take into consideration this setting is important to assert the ability of our software to carefully administrate the balance between prediction of the energy deltas for the morning, and estimate of the gap for the rest of the day.

Figure 11 shows how in the first 2 days, where production is comparable to demand, it is able to understand that it is necessary to fully load the storage during the night in order to survive until the next day; whereas in the last 3 days depicted where production outweighs demand it is remarkable how the system understands that it needs to leave some headroom in the storage capacity to account for the surplus of production, that makes the storage load again. This behavior is clear from the curve of the SOC.

Instead, Figure 12 reports the behavior of the system during 5 particularly low-irradiated days in the month of January. In this situation the hard-limit on the savings that our optimization can provide is directly proportional to the

TABLE 6. Self-consumption support schemes in each country reported in [71].

Country	FIT	Note
Spain	-	The only income provided by the self-consumption installation is the savings in the electric bill
France	0.1240 €/kWh	This tariff premiums is granted for photovoltaic systems with an installed power of less than 100 kW.
Germany	0.1231 €/kWh	As of 2016, only systems under 100 kWp can obtain the premium. The other systems have to sell directly or participate in auctions.
Italy	0.1000 €/kWh	The self-consumption is allowed for all installation sizes. For example, in the case installations with power equal to or less than 500 kWp (as in the the case-study proposed by this paper), a net-metering was changed to the so-called Scambio Sul Posto (SSP). This mechanism, as explained in [72], differs from the remuneration granted to the EC, which corresponds to 0.1100 €/kWh
Finland	0.0450 €/kWh	Furthermore, homeowners can get a tax deduction for the installation work of a photovoltaic system (45% of the labor cost, including fees).

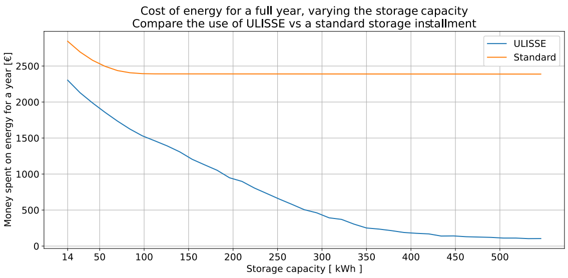

FIGURE 13. Results applying the ULISSE software: Difference in a full year of expenses using ULISSE vs a standard system.

size of the storage, as it can be clearly understood from the chart.

Indeed, the model is correctly able to estimate that production will not be able to keep up with demand and therefore the storage gets fully charged every night; however it is not enough to supply energy for all the remaining day. Therefore if one wants to further reduce the cost of the bill the only solution is to increase storage capacity, provided that that is compatible with the desired time to break-even.

Moving to the analysis of saving on the bills, the curves in Fig.13 are devoted to show practically, at the end of the day what kind of advantages our software can provide. The value of capacity that has been utilized to generate all the charts reported in this last Section, as already stated, corresponds to the use of 14 unit of the Sonnen standard module, accounting for a total capacity of $14 * 14\ kWh = 196\ kWh$. The saving that can be obtained using this capacity, with respect to a standard installment amounts to 1398 € on the total cost of energy for the building on a yearly basis, so approximately 70€ per household. Reading from the graph it also emerges what was reasoned upon looking at Fig.12; that is how having consistent under-production over several days creates a bottleneck on the savings that depends on the capacity of the storage. This last chart shows how the value of capacity at which the obtainable saving plateaus is beyond 400 kWh, where a saving of over € 2200 is registered, so an increase in savings of 60 % when doubling capacity.

The chart also shows how for a standard system, the ability to exploit storage capacity is really limited to the situations in which productions outweighs demand, and therefore once the storage is capable enough to store the highest daily delta in production, increasing it will not provide any more advantages.

Contrarily, the solution proposed by this paper will provide a consistent saving on the total bill. It is important to underline how the implementation of the proposed solution comes with no additional cost, and it is therefore very easily pluggable-in to whatever remote control system the storage providing company has already in place.

C. SELF-CONSUMPTION REMUNERATION MECHANISM

Furthermore, European governments have activated remuneration policies to incentive green-energy self-consumption, which can be variable or fixed, working with different mechanisms [70]. Note how the economic saving computed in the previous section does not take into account these policies, which vary nation by nation. For example, [71] explains how the remuneration mechanism works in Spain, France, Germany Italy, United Kingdom, and Finland. It highlights how, in the different countries, the granted feed-in-tariff (FIT) can strongly vary country by country, as also the plant size for which the remuneration can be applied. The different self-consumption support schemes described by [71] have been reported in table 6.

This mechanisms of remuneration have not been taken into account in the economical analysis previously proposed because strongly depends on the nation considered, but also on the policy in effect at the time when the project is installed. This kind of variable aspect cannot be modelled as done for the expected reduction cost, weakening the validity of the results. For this reason, this further economic instruments have not been considered, but they have been proposed for the economic push that they bring to the economical feasibility of the solution proposed.

The proposed methodology can also be integrated with electricity demand management algorithms. In this sense, EVs represent an opportunity on both the demand and supply side, as they could positively influence the effectiveness of the storage system, and brings to further economic benefits in terms of remunerations as well. Reference [73] shows how

PV systems with BESS can operate in vehicle-to-grid (V2G) and grid-to-vehicle (G2V) modes, increasing the efficiency of the whole system. The integration of such modes in the proposed case study could mean higher economic savings, thanks to the revenues coming from the sale of energy to grid (and then to the EVs).

Lastly, the Ancillary Service Market (MSD) represents another opportunity for accessing to remuneration mechanisms for energy system with storage, that can give flexibility in power fed into the grid and the load demanded from the grid [74]. The TSO usually pays for such flexibility (on demand) because it helps to balance the local grid frequency. In order to consider the mechanism of the MSD into the optimization, several trade-off phenomena have to be considered, such as:

- the additional costs necessary to meet the technical requirements needed to enter market such as the MSD;
- the model of the possible revenues from this type of electricity market;
- an estimation of when the TSO might require a demand/production shift.

In summary, this paper proposes an optimisation strategy that takes into account the economic benefits that could be derived from the electricity bill based on the hourly rate. Moreover, the proposed methodology could be extended to take into account other phenomena that allow access to other remuneration mechanisms, thus increasing the economic profitability of the adopted optimisation strategy.

VI. CONCLUSION

In the context of energy transition in a densely populated urban environment, this work aimed to introduce a hybrid control strategy based on physical models of system components and machine learning methods for predicting electrical load and RES production. In order to optimize the profits that can be obtained by installing energy storage, this control strategy will exploit both the photovoltaic production and the energy price at the time of use. The application of the proposed methodology has a number of advantages. Firstly, it maximizes the use of RES; secondly, it can reduce the final energy price perceived by residential customers; finally, it can encourage the installation of BESS, which can be used to increase the stability of the electricity grid.

The economic analysis shows that our proposed method is a profitable investment today, even taking into account the cost of the storage system and the PV installation. The break-even point will indeed be reached in thirteen years, with the costs of the storage systems, which represent a large part of this investment, playing a key role.

The presented work evaluated the economic and energetic feasibility of an Computational Intelligence-based system for an efficient management of a Battery Energy Storage. Additional studies can investigate the possibility of exploiting this system also for providing grid services for improve its stability: this additional analysis can highlight new possible business that can further enhance the economic feasibility of the proposed system.

Given Bloomberg's forecast for the cost of the storage systems, we obtained that in the following years, especially from 2026, a more convenient and fruitful investment could be reached leading to break-even in less than six years. This process could be expanded exponentially over the next few years as storage costs continue to decrease. However, this trend can be accelerated with solutions for the optimization of energy management, and, in this sense that the point comes to the impact of our approach. Once the prediction system was implemented and trained, the economic results confirmed the efficiency of the proposed method even under completely realistic conditions. In summary, it is able to increase the percentage of energy purchased at the minimum price from 25% to 91% and reduce the electricity bill by 55% compared to the most current solution on the market. And all this without additional costs and while stabilising the grid.

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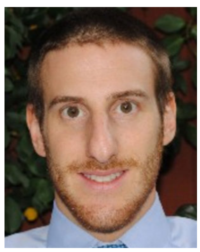

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