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A mixed-integer programming model for the optimal energy management in smart buildings

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A mixed-integer programming model for the optimal energy management in smart buildings

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Abstract The topic of energy management has always been at the center of numerous scientific studies, but in recent years, due to historical, political, and climatic events, it has emerged as a priority that cannot be overlooked. In this context, mathematical programming of resources plays a key role—an indispensable tool for managing any type of limited resource, capable of minimizing costs and maximizing the efficiency of energy systems. The aim of this work is to demonstrate how optimized energy management in Smart Grids offers advantages both in economic terms and in the operational efficiency of the system.

Keywords: Smart Building, Mixed-Integer Linear Programming, V2G (Vehicle-to-Grid)

1 Introduction

This work falls within the context of Smart Building (SB) management, aiming to achieve nearly Zero Energy Buildings (nZEB) through the use of new solar energy production technologies, energy storage via BESS systems, and V2G technology from electric vehicles. These approaches yield significant results in terms of reducing environmental pollution, improving the efficient use of the system, and generating financial returns. The latter aspect is particularly crucial, as the goals set by the European community will never be achieved unless adopting green technologies also proves economically advantageous for those bearing the associated costs.

A key concept in this work is that of distributed generation. This term refers to electricity generation systems - primarily from renewable sources - located along the distribution line, which has traditionally been modeled solely as a load and therefore did not account for such possibilities. What makes these systems particularly interesting is not only the growing focus on sustainability, but also their potential as tools to reduce the imbalance between energy supply and demand, thereby lowering the high costs associated with purchasing increasing amounts of energy.

This new technology, while offering significant opportunities, also presents challenges due to the stochastic nature of the energy fed into the grid from renewable sources. This leads to the concept of Smart Buildings (SB), which aim to promote local consumption or storage of energy generated from renewable sources rather than feeding it back into the grid.

Another goal of Smart Buildings is to prevent overloading the distribution network with electric vehicle charging—a current issue that, combined with the limited range achievable on a single charge, still represents a barrier to widespread electric vehicle adoption. However, the need to replace traditional vehicles with electric ones is increasingly urgent, not only for environmental reasons but also for economic ones, as the electric vehicle market has experienced remarkable growth in recent years.

1.1 Literature review

The climate emergency of recent decades and the growing need to optimize resources are increasingly becoming central themes in scientific research. The idea for this work stems from an in-depth study of this topic as addressed in the literature.

The research conducted is based on several studies presented in scientific articles, identifying their innovations and resolving their limitations. The mathematical model developed is based on the one proposed in [1], which considers a large-scale Smart Building equipped with a photovoltaic system and a Battery Energy Storage System (BESS), along with the presence of numerous V2G-enabled electric vehicles. In that article, the model is applied over a very short time horizon (five afternoon hours), and many aspects—successfully introduced and modeled in the present work—are not taken into account.

In [2], a Smart House with a single V2G-enabled vehicle is considered. The novelty lies in modeling the vehicle's arrivals and departures as a Markov chain. Furthermore, [2] presents the average consumption trends in residential buildings, highlighting a peak that is overlooked in other articles, thus demonstrating the need to extend the model's application to at least a 24-hour period.

In [3], a solution algorithm was proposed to maximize the efficiency of a storage system. From this work, both average charge/discharge values and several insights were drawn, which have been incorporated into the heuristic proposed to demonstrate the effectiveness of the model.

In [4], the main issues related to photovoltaic systems are discussed—such as the stochastic nature of solar irradiance and its low availability in winter—challenges that this work aims to address through model development.

In [5], the issue of optimal battery sizing in a smart home is addressed using convex programming, a method that led to proper sizing of the storage system when the model was applied to a real-world case in Italy.

In [6], game theory is applied using the Stackelberg method, highlighting the need for a trade-off between the energy provider and users—a theme that is also considered in the model proposed in this work, albeit without the use of game theory.

The present work aims to improve upon and address some of the current limitations in this field. The innovations that distinguish this study from existing models in the literature lie in the fact that:

- The model was applied over a 24-hour period, taking into account the average daily annual energy consumption.
- A model was used to track the presence of vehicles within the Smart Building, based not only on their presence or absence, but also on their state of charge.
- The model was also applied to small-scale case studies, demonstrating its validity and accuracy by using real, empirically measured field data.

In this work, the Smart Building is considered as a single user by aggregating the consumption of multiple apartments. The V2G electric vehicles were initially treated as identical, but were later differentiated and reduced in number based on a real-world case study.

This paper is structured as follows. In Section 3, the problem will be defined along with the entities involved and the reasons why it can be formulated as a mixed-integer linear programming problem. Section 4 will present the mathematical formulation of the model. In Section 5, various scenarios will be analyzed and compared to highlight the significant differences between non-optimized and optimized scheduling. Section 6 will show the results and draw conclusions, introducing potential future developments and initiating a possible investment analysis to evaluate profitability for users. Finally, Section 7 will demonstrate the application of the model to a smaller-scale Italian case, illustrating how programming is relevant not only for large-scale systems but also for small and medium-sized contexts, which are far more common in Italy.

2 Problem under consideration

The main objective is to minimize the power demand that the Smart Building places on the grid and to integrate electric vehicles in such a way that their charging does not congest the electrical network. This Smart Building is equipped with a photovoltaic system that is insufficient to cover the entire power demand, a Battery Energy Storage System (BESS), and a charging system for V2G-enabled electric vehicles. The BESS, whose technical specifications are reported in [7], is necessary because solar irradiance is not consistently available throughout the day. This storage system has the following technological limitations:

Type of vehicle	**Storage Capacity**	**Charge Power**	**Discharge Power**
BESS-1000L	50 kWh	6.3 kWh	5.67 kWh

Table 1: Technical specifications of the BESS battery used in the article

The constraint that makes the choice of charging and discharging these storage systems critical lies in the fact that when the BESS is charging, it cannot supply energy to the users. Consequently, users must rely alternatively or simultaneously on energy provided by the vehicles and the grid, resulting in increased costs. Therefore, deciding when to charge and discharge the BESS is not trivial. The energy stored in the batteries comes from the photovoltaic system and, if necessary, from the grid; hence, in this work, it is considered sustainable energy. Nevertheless, in the mathematical formulation presented in Section 3, the charging of the BESS is treated as energy that increases the power demand from the grid.

V2G vehicles represent the technological innovation introduced in recent years. These are special electric vehicles that allow both the storage of energy from renewable sources or the grid, and the supply of their excess stored power back to the home network, acting as alternative storage units to the BESS.

In the case study, a simplifying assumption was made in the model by using 12 identical V2G vehicles—one per apartment—selected based on a market survey (the vehicle's technical specifications are reported in [8]). The following table presents the construction data of the chosen model and the related technical characteristics used within the model:

Type of vehicle	**Storage Capacity**	**Charge Power**	**Discharge Power**
BMW i3 94 Ah	27.2 kWh	3.7 kWh	3.33 kWh

Table 2: Technical specifications of the V2G vehicles

Initial state-of-charge conditions of the vehicle batteries and the BESS must be taken into account. For this purpose, Table 3 reports the initial conditions of all the elements.

Table 3: Initial state-of-charge conditions of the elements

SOC_1^0	SOC_2^0	SOC_3^0	SOC_4^0	SOC_5^0
38% $\mathrm{SOC}_1^{\max}$	40% $\mathrm{SOC}_1^{\max}$	37% $\mathrm{SOC}_1^{\max}$	70% $\mathrm{SOC}_1^{\max}$	40% $\mathrm{SOC}_1^{\max}$
SOC_6^0	SOC_7^0	SOC_8^0	SOC_9^0	SOC_{10}^0
47% $\mathrm{SOC}_1^{\max}$	80% $\mathrm{SOC}_1^{\max}$	37% $\mathrm{SOC}_1^{\max}$	40% $\mathrm{SOC}_1^{\max}$	43% $\mathrm{SOC}_1^{\max}$
SOC_{11}^0	SOC_{12}^0	SOC_B^0	$\mathrm{SOC}_B^{\max}$	$P_g^{\max}$
78% $\mathrm{SOC}_1^{\max}$	56% $\mathrm{SOC}_1^{\max}$	50% $\mathrm{SOC}_B^{\max}$	100% Capacity	70

The energy demand of the condominium and the power supplied by the photovoltaic system are known in advance. Moreover, the availability of electric vehicles is determined not only by their physical presence but also by a sufficiently high battery state of charge.

3 Mathematical formulation

Now that the elements of the problem and the objective of the model have been defined, we can proceed with the mathematical formulation by specifying the parameters, variables, and indices. The resulting optimization problem is a Mixed Binary Linear Programming (MBLP) problem. These types of problems significantly increase the complexity of finding solutions, as the solution space becomes much larger compared to a binary problem with n variables, thus prolonging computation time due to the exploration of the problem's decision tree.

Nevertheless, an MBLP is able to represent reality more accurately and is ideal for making decisions based on discrete variables that influence continuous variables — in this case, the charging process and the state of charge of vehicle batteries.

Firstly, Table 3 presents the nomenclature used in this work. In the referenced article by the authors, a different solver, CPLEX, was used — a tool commonly employed in industrial settings, but less efficient for MBLP problems. The decision to use a different solver was not only driven by the intention to verify the correctness of the model proposed in the literature, but also to enhance code interpretability and computational speed when comparing different scenarios. This speed is made possible through the relaxation phase and the parallel exploration of decision tree branches via the Branch and Bound method.

Indices	
i	Indices of the time periods throughout the day
j	Indices of electric vehicles
Parameters	
τ	Length of the interval in each period i
P_i^g	Active power drawn from the grid during period i (kW)
c_i	Penalty factor based on available photovoltaic power relative to consumption in period i
P_i^{sb}	Active power related to the Smart Building load forecast in period i (kW)
P_i^{pv}	Active power related to the forecasted photovoltaic production in period i (kW)
$P_{ch\_ev}^j$	Active power related to the charging process of EV j (kW)
$P_{dis\_ev}^j$	Active power related to the discharging process of EV j (kW)
σ_i^j	Binary parameter based on the travel forecasts of EVs, representing the connection of EV j in period i
P_{ch_B}	Active power related to the BESS charging process (kW)
P_{dis_B}	Active power related to the BESS discharging process (kW)
SOC_j^{max}	Maximum SOC of EV j, assumed constant in all periods
SOC_j^{min}	Minimum SOC of EV j, assumed constant in all periods
$SOC_j^{min\_final}$	Minimum final SOC of EV j, assumed constant in all periods
SOC_B^{max}	Maximum SOC of the BESS, assumed constant in all periods
SOC_B^{min}	Minimum SOC of the BESS, assumed constant in all periods
P_g^{max}	Maximum power that the grid can supply to the building, assumed constant in all periods (kW)
Variables	
α_i^j	Binary variable representing the charging process of EV j in period i
β_i^j	Binary variable representing the discharging process of EV j in period i
α_i^B	Binary variable representing the BESS charging process in period i
β_i^B	Binary variable representing the BESS discharging process in period i
SOC_i^j	SOC of vehicle j at the beginning of period i
SOC_i^B	SOC of the BESS at the beginning of period i

Table 4: Nomenclature of the indices, parameters, and variables of the proposed problem

3.1 Objective function

The aim of the model is to minimize the power drawn from the grid and thus paid by the users over the course of a day. In fact, users resort to using the grid when photovoltaic energy is not sufficient to meet their demand (a very frequent situation during hours with low solar irradiance), and when the BESS and electric vehicles are not sufficient or available to supply energy to the building. The objective function minimized in the problem is:

$$P_i^g = P_i^{sb} - P_i^{pv} + \sum_{j=1}^{n} (P_{ch\_ev,j}^i \cdot \alpha_i^j - P_{dis\_ev,j}^i \cdot \beta_i^j) \cdot \sigma_i^j + P_{ch\_B} \cdot \alpha_i^B - P_{dis\_B} \cdot \beta_i^B$$

This expression makes it clear that, in a given time interval i, the power drawn from the grid P_i^g corresponds to the balance between the power demand of the building P_i^{sb}, the power generated by the photovoltaic system P_i^{pv}, and the total power exchanged by the n vehicles present in the condominium parking lot and connected to the network[1].

It might appear that vehicle charging occurs only through the grid, but as stated multiple times in Chapter 1, vehicles also recharge using photovoltaic energy. However, when they are charging, they cannot contribute to reducing the power demand from the grid, and the model penalizes such a situation by increasing the value of the objective function in case of vehicle charging. In this way, the solver tends to minimize such charging periods, as long as the constraints on the vehicles' battery state of charge are respected.

A similar reasoning applies to the last two components of the P_i^g function. Indeed, it might also seem that the BESS charges via the grid, but this modeling choice was made to minimize charging periods of the accumulator while still respecting the minimum state of charge constraints.

Since the model aims to optimize the most appropriate timing for the charging and discharging processes of both the BESS and EVs, a parameter c^i is introduced to multiply P_g^i, defined as follows:

$$c^i = \frac{(P_i^{sb} - P_i^{pv})}{\min(P^{sb} - P^{pv})}$$

This parameter increases as the difference between the required power and the power supplied by the photovoltaic system grows. In Figure 1.1 of Chapter 1, it can be seen how this value reaches its maximum at 17:00,

[1] In the summation that defines this total, each term can be positive if the vehicle is charging, or negative otherwise

which causes an increase of P_i^g in the objective function at $i = 17:00$; this is taken into account by the solver, which will consequently tend to discharge the vehicles and the BESS at the time i when photovoltaic availability is lowest and demand is highest.

It can be noted that when the numerator and denominator are equal, P_i^g will not be penalized, and the solver will understand that at that time the difference between power demand and photovoltaic production is minimal, thus charging the BESS and EVs.

Finally, to consider the total grid power to be minimized, all hourly contributions from 1 to I are summed:

$$\min \sum_{i=1}^{I} P_i^g \cdot c^i$$

Once the objective function is defined, the constraints on the variables imposed by the physical limits of the problem under consideration are taken into account.

3.2 Physical constraints of the problem

This paragraph formulates the physical constraints of the vehicles and the BESS in two separate subparagraphs, constraints that will be applied at each time interval of duration τ.

3.2.1 Physical constraints of the vehicles

It is necessary, first of all, to set the maximum capacity limits of the vehicles' batteries in each time period:

$$SOC_i^j \leq SOC_j^{max} \quad i = 0, ..., I$$

These continuous variables must be updated at every time instant i; this update is ensured by the constraint:

$$SOC_{i+1}^j = SOC_i^j + \sigma_i^j \cdot (P_{ch\_ev,j}^i \cdot \alpha_i^j - P_{dis\_ev,j}^i \cdot \beta_i^j) \cdot \tau$$

Furthermore, at time $i = 0$ the initial state of charge of the vehicles' batteries must be defined; these values were provided by the authors and have been incorporated into the model implementation code. A necessary condition for this scheduling to be applicable in reality is that the battery charge of the vehicles never falls below a certain threshold so that users can always be able to use the vehicles at any time:

$$SOC_i^j \geq \sigma_i^j \cdot SOC_j^{min} \quad i = 1, 2, ..., I - 1$$

This minimum value can be chosen directly by the users; it is evident that if this minimum value is set to 100%, that vehicle will never contribute to reducing the power drawn from the grid. To avoid this, an additional constraint has been introduced that imposes a predetermined final SOC, so that a user can allow their vehicle to be discharged during its unused period but find it at the desired state of charge afterward (even at 100%):

$$SOC_I^j \geq SOC_j^{min\ final}$$

where I can be either common or different for each user. Finally, the physical constraint must be imposed that a vehicle cannot charge and discharge power simultaneously, and that the decision variables α and β depend on the presence or absence of the vehicle in the condominium parking lot:

$$\alpha_i^j + \beta_i^j \leq \sigma_i^j$$

The decision variables must be binary variables:

$$\alpha_i^j \in \{0, 1\}$$
$$\beta_i^j \in \{0, 1\}$$

where:

$$\alpha_i^j = 1: \text{ vehicle } j \text{ is charging during period } i;$$
$$\alpha_i^j = 0: \text{ vehicle } j \text{ is not charging during period } i;$$
$$\beta_i^j = 1: \text{ vehicle } j \text{ is discharging during period } i;$$
$$\beta_i^j = 0: \text{ vehicle } j \text{ is not discharging during period } i.$$

3.2.2 Physical constraints of the BESS

As with the vehicles, there are also capacity constraints for the accumulators that need to be translated into mathematical formulas:

$$SOC_i^B \leq SOC_B^{max} \quad i = 0, ..., I$$

This limit is imposed by the technical datasheet and by the chosen accumulator model on a case-by-case basis, and as with the vehicles, the state of charge and discharge must be updated at every time instant $i = 1, ..., I$:

$$SOC_{i+1}^B = SOC_i^B + (P_{ch\_B} \cdot \alpha_i^B - P_{dis\_B} \cdot \beta_i^B) \cdot \tau$$

Considering that lithium batteries cannot be completely discharged without damaging their capacity, a minimum state of charge constraint is added, not only to prevent such damage but also to ensure a safety amount of energy in case of power outages.

$$SOC_i^B \geq SOC_B^{min} \quad i = 1, 2, ..., I$$

Finally, in this case as well, it is necessary to impose the constraint of energy unidirectionality, meaning the BESS cannot charge and discharge simultaneously:

$$\alpha_i^B + \beta_i^B \leq 1$$

together with the constraint that defines the variables α and β as binary decision variables:

$$\alpha_i^B \in \{0, 1\}$$
$$\beta_i^B \in \{0, 1\}$$

for which, in terms of decisions, it holds that:

$$\alpha_i^B = 1 : \text{ the BESS is charging in period } i;$$
$$\alpha_i^B = 0 : \text{ the BESS is not charging in period } i;$$

$$\beta_i^B = 1 : \text{ the BESS is discharging in period } i;$$
$$\beta_i^B = 0 : \text{ the BESS is not discharging in period } i.$$

3.2.3 Contractual constraints

Finally, it is necessary to impose a contractual limit on the power supplied by the grid. This limit is agreed upon during negotiations between the electricity provider and the condominium. In the Portuguese case, this value is 70 kW for the entire condominium; in Italy, this limit is set for each apartment. This topic will be explored in more detail in the following chapters, but the general mathematical expression to formulate this constraint is as follows:

$$P_i^g \leq Pg^{max} \quad i = 1, ..., I$$

4 Analysis of different scenarios

This paragraph will present three different scenarios. The baseline scenario (referred to as scenario 0) in which there are no electric vehicles or battery storage, and where the power drawn from the grid must be reduced. The second scenario applies a reasoned heuristic by introducing electric vehicles and the battery storage, but without applying the proposed model. The final scenario is where the model is applied and the MILP is solved using GUROBI via AMPL.

4.1 Scenario 0: Initial case

The following scenario considers a situation where the only renewable source used to reduce the power drawn from the grid is photovoltaic energy, representing the baseline scenario with no optimization applied. The results of this situation, which need improvement, are shown in Figure 8. In this scenario, no electric vehicles are present; only the contribution of photovoltaic energy (shown in green in Figure 1) reduces the power drawn from the grid (shown in red in Figure 1). The value of the objective function in this case is:

$$P_g^{tot} = 651.4 \ \ kWh$$

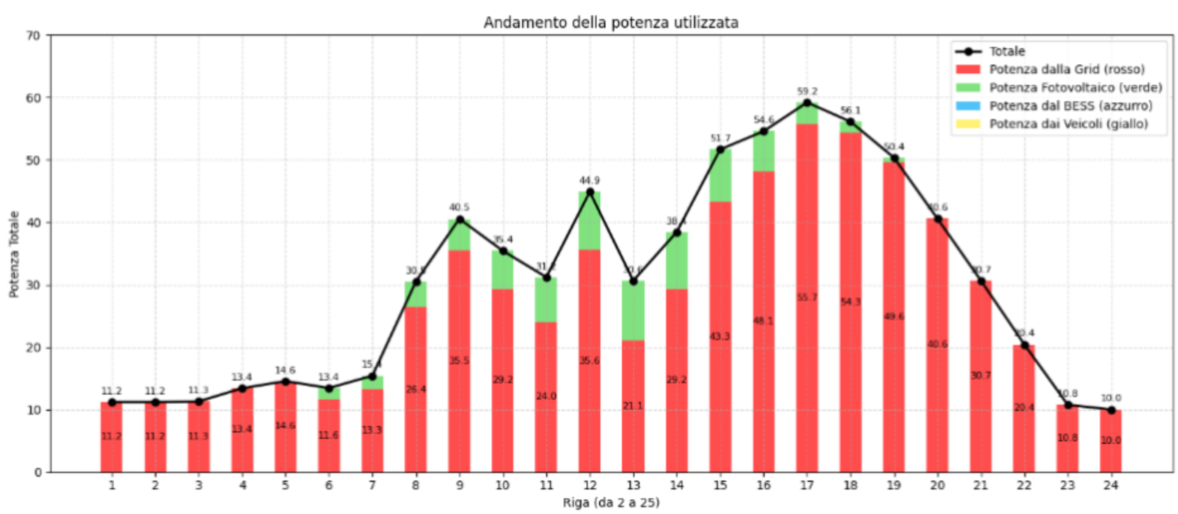

Figure 1: Trend of the power supplied by the grid in scenario 0

4.2 Scenario 1: Reasoned heuristic

In the following scenario, a design of a heuristic algorithm was proposed to find a good feasible solution of high quality:

"The vehicles are charged during the periods of least likely use and are discharged during the peak energy demand periods of the day. The BESS is used when photovoltaic energy is not available; otherwise, it is charged and not used unless necessary."

By applying this method, the resulting scenario is shown in Figure 2, where it can be observed that the charging of the vehicles has been scheduled for the time period preceding their use (assumed to be at 7:00 AM) and their discharging has been scheduled for the evening hours, when demand is highest. Regarding the battery storage, its charging and discharging periods align with the previously mentioned heuristic. From a mathematical perspective, this scenario presents an interesting result to compare with the initial scenario without vehicles and batteries:

$$P_g^{tot} = 666,3 \ \ kWh$$

This power is higher compared to scenario 0 because electric vehicles have been introduced, which require a significant amount of energy compared to the case where these vehicles are absent. Through this heuristic, it was possible to mitigate the overload, but the result remains unsatisfactory.

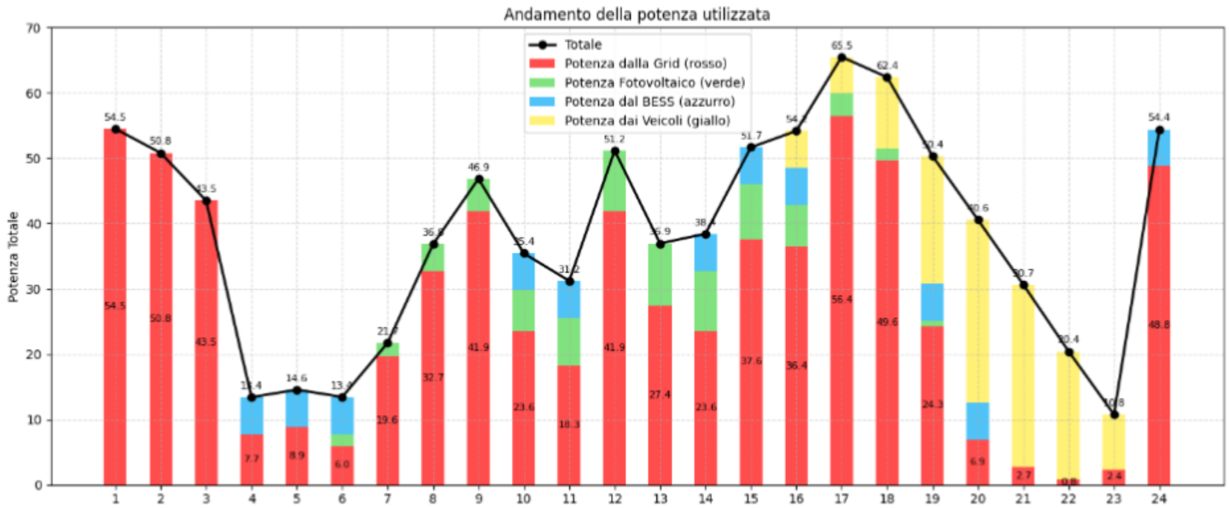

Figure 2: Trend of the power supplied by the grid in scenario 1

4.3 Scenario 2: Optimal solution of the constructed model

In this scenario, the results obtained by applying the proposed mathematical model are shown in Figure 3. The solution achieved demonstrates a significant reduction in energy demand from the grid:

$$P_g^{tot} = 590.8 \;\; kWh$$

In this scenario, it can be observed that a state has been reached where electric vehicles are integrated perfectly without overloading the grid, and the batteries act as energy buffers when photovoltaic production is insufficient to meet the condominium's demand. This result demonstrates the fundamental importance of optimization in managing the integration of electric vehicles within the residential grid. Through the sole use of mathematical programming, it has been possible to achieve a scenario that matches the utility and efficiency of the heuristic situation, improving its effectiveness and solving the overload problem, with consequent financial benefits for the users.

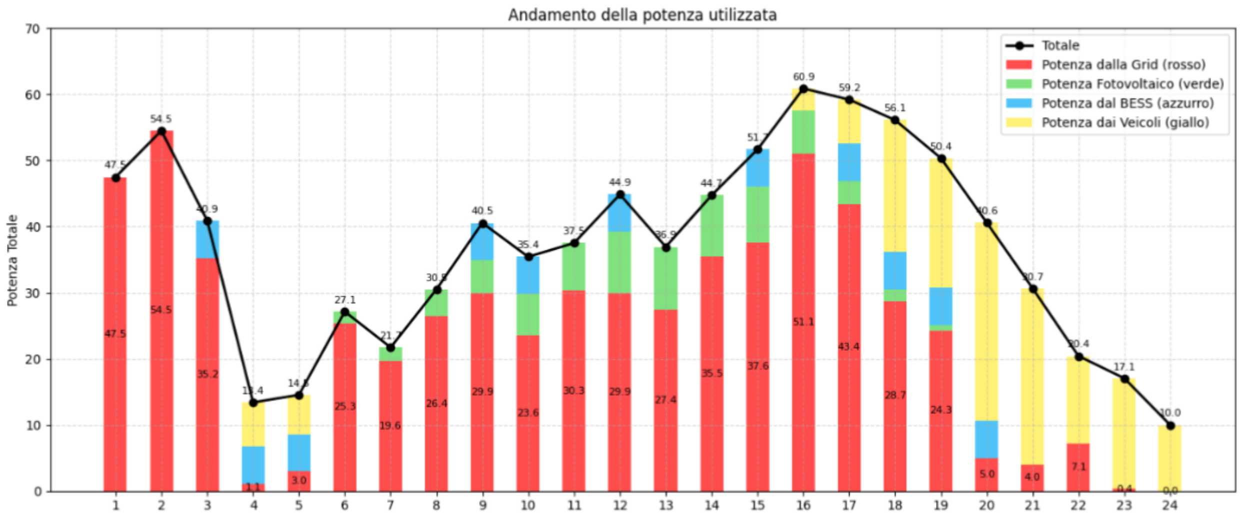

Figure 3: Trend of the power supplied by the grid in scenario 2

5 Obtained results

The results achieved in this work, through the analysis of the various previously presented scenarios, are multiple. First of all, there is a reduction in grid demand equal to 60.6 kiloWatts compared to the initial scenario without electric vehicles and without a battery storage system. Compared to the scenario with both vehicles and storage using a heuristic, the demand difference is 75.5 kiloWatts (an even more effective result). These outcomes are positive from both perspectives.

5.1 Benefit for users

Comparing scenario 2 with the previous ones, a significant decrease in the energy demand from the electricity supplier can be observed, despite the introduction of vehicles replacing their fuel with electric energy. Considering an average energy price of €0.23/kWh, this result translates economically into an annual saving shown in Figure 4, amounting to €423.95 saved per apartment compared to scenario 0 and €528.18 compared to scenario 1, without minimally affecting the utility of the vehicles.

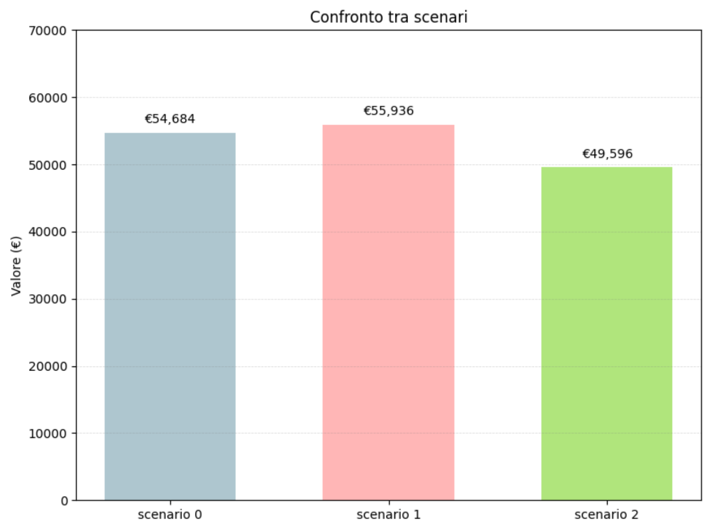

Figure 4: Financial analysis of the different scenarios

Therefore, it is economically advantageous in the long term to introduce V2G technology vehicles, combining them with the use of photovoltaic systems and batteries.

5.2 Benefit for the energy provider

From the perspective of the electricity supplier, the main advantage of this scheduling is that it avoids congestion of the grid during the charging of V2G vehicles. Analyzing the different demand curves of the various scenarios in Figure 5:

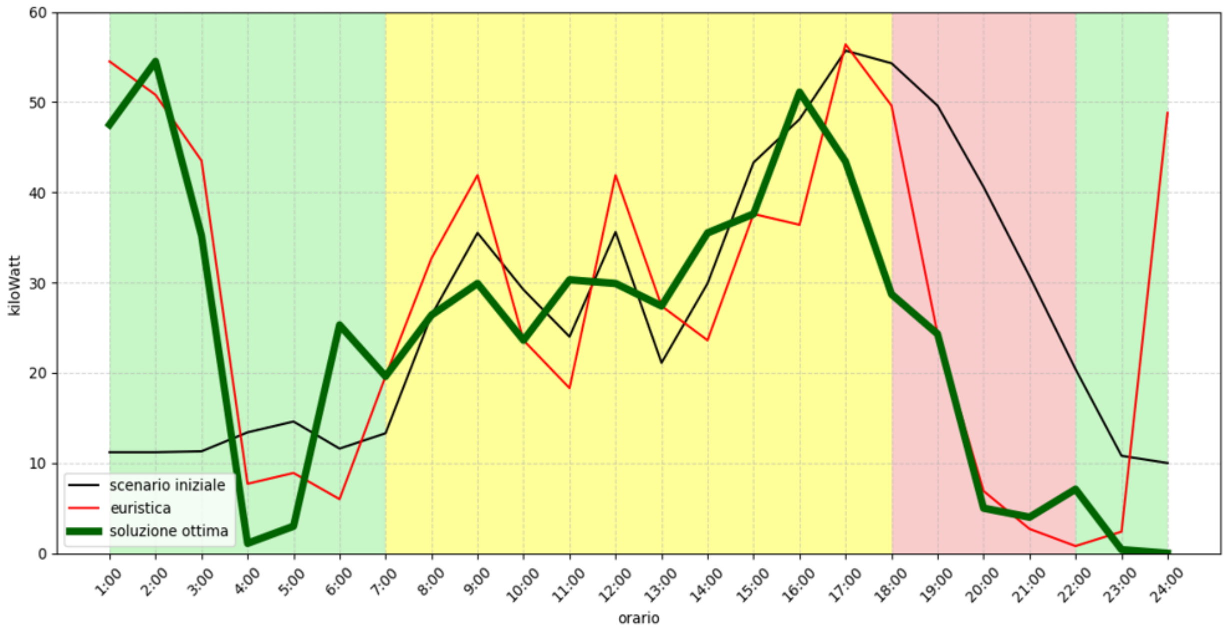

Figure 5: Trend of energy demand by users

We can derive several advantages:

- The peak power demand shifts away from the critical time window for the energy market (18:00-22:00).
- Electric vehicles are charged during time slots when the energy demand is less congested (the green areas in the graph).
- The power demand in the intermediate time window (from 7:00 to 18:00) appears smoother and with lower variance. This result is beneficial for the energy supplier, who desires a request as regular as possible during those hours.

6 Application to a real case

The proposed mathematical model achieved highly effective results on a large-scale Smart Building. Another aspect addressed in this work was the application of the model to a real case in Italy involving a smaller-sized Smart Building.

To estimate the power demand of the condominium, empirical data were collected over a limited number of days through hourly self-reading of the apartment meters. Subsequently, averages were calculated across the different days. Finally, an overall average was computed and compared with data provided by ARERA (Italian Regulatory Authority for Energy, Networks and Environment) in [9].

This choice was made because the number of measurements was limited; therefore, if the collected data do not significantly differ from the values published by the national authority ARERA, they can be considered sufficient. To verify that the two samples are not statistically significantly different, a comparison of means was conducted, considering that the data are:

- Independent: Each apartment is independent, and the residents within it are random.
- Balanced: in both cases, the full 24 hours of the day were considered.
- Gaussian: for this analysis, the use of the Q-Q plot was chosen, shown at the bottom of the comparison between means in Figure 4.5. This test shows only slight deviations from normality at the tails but reveals a sufficient visual adherence to normality.

Furthermore, the electric vehicles are no longer all identical and equal in number to the apartments; rather, they are fewer (only 5 out of 9 apartment residents) and each different from the others. Finally, price discrimination based on time-of-day bands was also introduced.

6.1 Scenario 0: Initial case

The baseline scenario to which the model is applied is as follows:

The cumulative power requested from the grid in one day results in:

$$P_g^{tot} = 66.9 \ \ kWh$$

6.2 Scenario 1: Reasoned heuristic

By applying the same heuristic reasoning described in paragraph 4 for the previous Smart Building case, the resulting scenario is as follows:

This scenario might at first glance seem significantly worse, but in reality, the power demanded from the grid is:

$$P_g^{tot} = 82.2 \ \ kWh$$

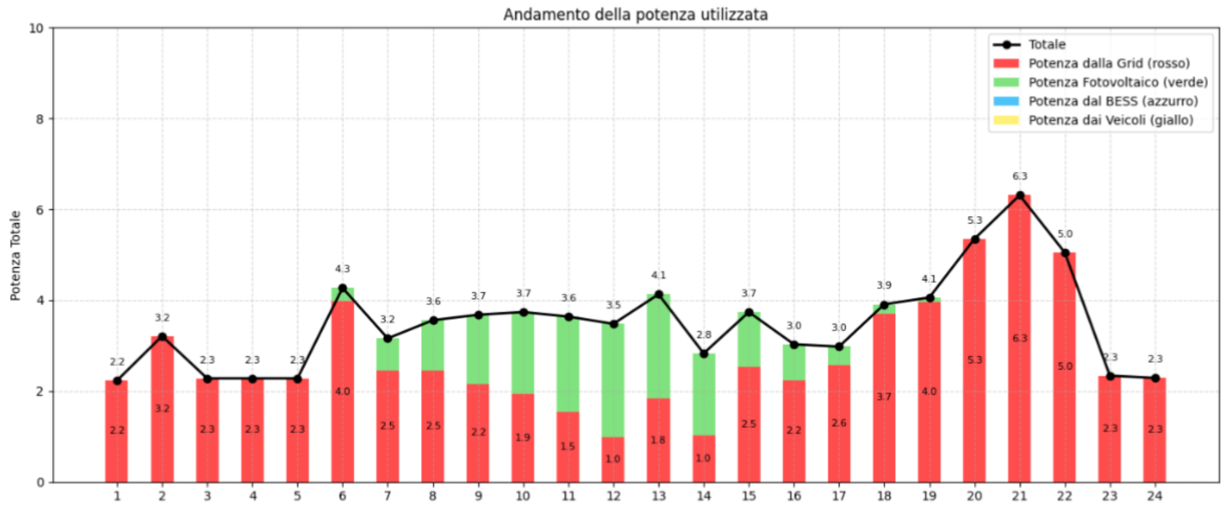

Figure 6: Power trend in scenario 0 in Italy

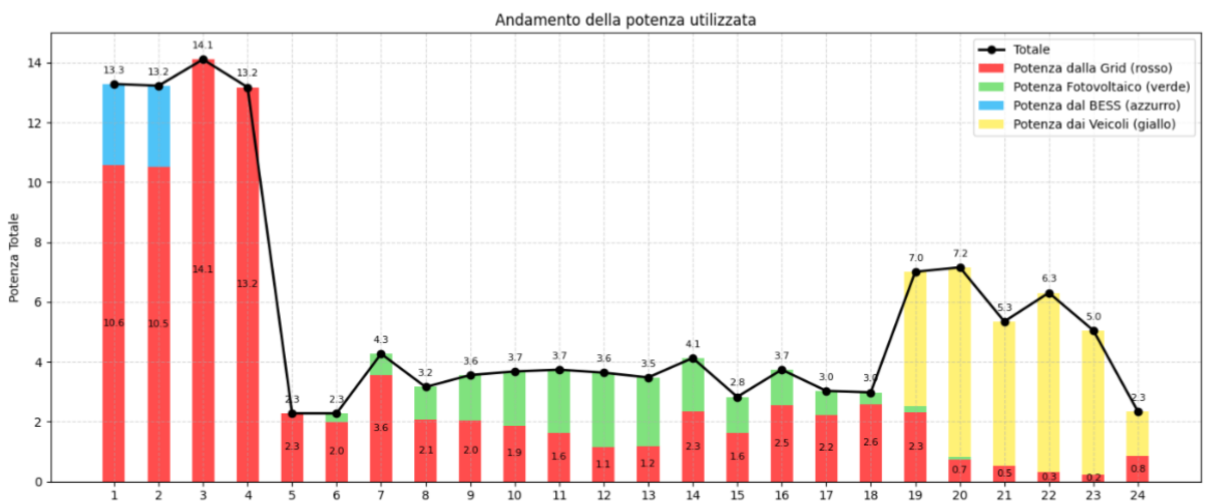

Figure 7: Power trend in scenario 1 in Italy

Moreover, the energy peaks occur during nighttime hours when (according to the profile provided by ARERA) the regional user energy demand, where the data collection was conducted, is at its minimum. The problem with this solution is the congestion of the electrical grid in Italy due to the charging of electric vehicles. Furthermore, the power requested from the grid is higher compared to the initial case without vehicles, leading to increased monthly costs for users and making the investment not cost-effective.

6.3 Scenario 2: Optimal solution

This scenario shows the significant results obtained through the use of an optimization model implemented in AMPL. The model not only scheduled when to charge and discharge the vehicles and the BESS, but also considered the most convenient times to do so. The result is shown in Figure 8.

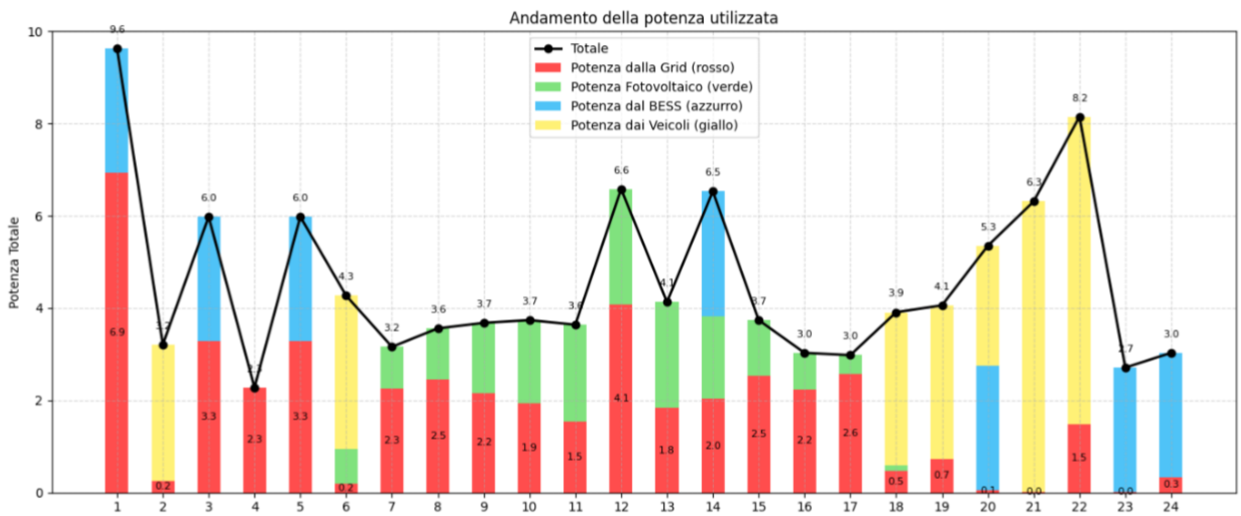

Figure 8: Power trend in scenario 2 in Italy

In this scenario, the most performant result of all was obtained, given the same availability and number of vehicles compared to the previous scenario:

$$P_g^{tot} = 44.9 \ \ kWh$$

This result demonstrates how, through optimized scheduling, electric vehicles represent a fundamental resource for energy savings. Indeed, as in the previous case study, the power saved from the grid compared to Scenario 0 amounts to 22 kilowatts per day, corresponding to an average annual savings of approximately €204.21 per apartment. Meanwhile, the power saved compared to Scenario 1 is about 37.3 kilowatts per day, with an average annual savings of €347.92.

7 Conclusions and future developments

7.1 Conclusions

In this work, the model developed in [1] was first reconstructed and extended to a time interval covering a full day. This made it possible to highlight the potential issues of a linear scheduling approach. The initial scenario featured a known demand profile to which a photovoltaic system was applied. This revealed that, in Smart Buildings, photovoltaic energy is insufficient to meet the entire user demand and that the introduction of electric vehicles may risk congesting the electrical grid. For this reason, BESS (Battery Energy Storage Systems) were introduced to make the electricity supply more flexible and to reduce demand peaks, along with the use of V2G (Vehicle-to-Grid) electric vehicles. A heuristic approach was initially presented, which could be considered reasonable: charging vehicles during hours of low user demand (from 00:00 to 04:00) up to their maximum allowable capacity, and then using the surplus energy in the evening. In this heuristic, the battery is discharged to smooth demand peaks and recharged at the most appropriate time, in order to exploit periods of minimum demand and balance the load. This heuristic allows for a result not significantly worse than the initial scenario, introducing electric vehicles into the home grid while not excessively increasing energy demand. The objective set at the beginning of this work was to achieve a better and more sustainable condition through an optimization model. This result was unequivocally achieved through the use of AMPL, by introducing V2G electric vehicles while simultaneously reducing the power demand in the building, both in the Portuguese and Italian cases. This demonstrates not only the usefulness of modeling but also the necessity of applying such an approach in both medium-scale case studies (Portuguese Smart Building) and smaller-scale ones (Italian condominium). The most evident difference between the two case studies lies in the direct proportionality between the size of the condominium and the benefits derived from optimization. Therefore, the necessity and importance of using a mathematical model in strategic decision-making have been demonstrated, both in large-scale systems and in systems of more modest size.

7.2 Future developments

Despite the positive results of this work, it is also appropriate to highlight the limitations identified in the model, which could serve as the basis for future developments.

A first aspect to consider is that V2G (Vehicle-to-Grid) technology is not yet widely adopted in Italy, unlike in other European countries. As explained in [10] and [11], this is mainly due to infrastructure and technical standards that are not yet aligned with the requirements of this emerging technology. Moreover, as V2G is an innovative charging method, there is currently a lack of clear regulations and a comprehensive fiscal framework. However, recent progress — such as the removal of double taxation on energy fed back into the grid — indicates potential for forthcoming regulatory advancements.

Another limiting factor lies in the current high cost of EV batteries. The degradation caused by frequent charge and discharge cycles may be unacceptable for EV owners, particularly in residential contexts where users without vehicles may still benefit from the stored energy provided by those who do own EVs.

Given the increasing popularity of car sharing, dealership offers such as "keep it or return it", and the growing trend of vehicle rentals, a promising future development could involve a business model where the EVs are not privately owned by residents, but rather leased. In this scenario, users would pay a subscription fee to access the vehicles, thereby generating mutual benefits for both the condominium and the vehicle provider. This model would not only reduce concerns about battery wear but also enhance optimization by standardizing vehicle types across apartments, allowing for a more accurate and efficient scheduling system.

Finally, the proposed model does not currently include a mechanism to simulate the arrival and departure of vehicles. This limitation was addressed in the present work by setting the parameter $\sigma = 1$ only when a vehicle is physically present at the condominium and its state of charge has returned to the level it had upon leaving. This approach ensures the vehicle's actual availability without overestimating its presence.

However, the drawback of this method is that it does not take into account the energy consumed to return the vehicle to its initial state of charge. Since this energy requirement is assumed constant across all scenarios involving vehicles, it was not included in the model. Nevertheless, this simplification does not pose a severe limitation: vehicles typically return at different times, minimizing the risk of grid congestion, and their range ensures that they do not require a significant energy input upon return.

A future development could involve constructing a simulation model that dynamically accounts for vehicle arrivals and departures, further improving the realism and effectiveness of the proposed scheduling framework.

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