Intelligent Energy Management System for Buildings with Renewables and Vehicle-to-Grid Charging

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***Abstract*—Electrical energy consumption is steadily growing worldwide, while renewable energy sources are gaining market share. In parallel, energy systems are undergoing a profound transformation, moving from a top-down hierarchical structure to a more decentralized model focused on the consumer, who will also produce, store and sell their own energy. This paper proposes a decision algorithm designed to help with the energy management task, in the context of a grid-connected household, with renewable energy production and electric vehicles (EVs). The algorithm makes use of several inputs such as energy consumption prediction, energy production output, EV battery state, and grid energy price in order to perform the optimal charge and discharge actions. The system's objective is to minimize the electrical bill of the household in several ways, one of them, by utilizing EVs batteries for energy storage. The proposed algorithm was validated in a simulated environment for 10 different households. In the several scenarios and test houses, the proposed approach attained an average decrease of 18.9% in the energy cost of the household.**

***Index Terms*—renewable energy, energy management, electrical vehicles, V2G, intelligent agents.**

I. Introduction

According to the UN, two thirds of the world's population is projected to live in urban areas by 2050 [1], with the residential sector accounting for 27% of the global energy consumption [2]. In recent years, renewable energies have undergone strong development. Public awareness of pollution from fossil fuels is increasing, and with it, the use of electric vehicles (EVs) has become increasingly popular, with EV sales soaring in the last few years [3].

According to Zhang *et al.* [4], Electric Vehicles could potentially provide a 45% reduction in carbon emissions compared to conventional internal combustion engine (ICE) vehicles after considering the energy cost of production, assembly, transportation and usage. To further strengthen this trend, new legislation restricting carbon emissions has been limiting the use of ICE vehicles. As an example, the UK plans to ban sales of new petrol and diesel cars from 2030 [5].

In the future, however, an excessive number of electrical vehicles can put a lot of pressure in the energy supply grid if their charging is uncoordinated. This is already a relevant problem today due to the peaks in electricity demand that put the grid under significant pressure [6].

Vehicle to Home (V2H) technologies and bi-directional chargers are solutions that can provide economic value in this context. They allow to provide the energy accumulated in an electrical vehicle's battery back to the household where the vehicle is connected to. In this scenario, the car can act as an energy storage system, but its uncertain availability must be considered. This feature of electrical vehicles can be of great value when considering optimizing energy usage (and local production) at different rates throughout the day. In this scope, there is an increasing effort to keep the energy distribution sustainable and to find ways of reducing its cost.

Several approaches have been pursued to integrate EVs and optimize energy usage in buildings, but these studies do not consider other variables, such as local renewable energy production. In [7] a machine learning approach is utilized to forecast vehicle availability in order to provide vehicle to home (V2H) service. Since the objective of the study was to reduce the user electrical bill, the charging strategy was optimized based on the vehicle availability forecast, by determining the optimal charging–discharging schedule based on the electricity cost at each period. The Electric Vehicle (EV) availability forecast was obtained using the Light Gradient Boosted Machine (LightGBM). The authors claim that the total electricity cost decreased to approximately half. However, this study only dealt with EVs and not with other variables such as energy production.

The work in [8] proposes a multi-agent approach to residential demand response, utilizing load forecasting. The objective is to have the electrical devices controlled by a reinforcement learning (RL) agent that, using information on the current electrical load and the load forecast for the next 24 hours, can meet the device electrical needs while staying within the transformer limits. In that study, only 9 devices are considered, more specifically, 9 EVs covered by a single transformer. Results show that RL is suitable for residential demand response. Agents mainly waited for low load periods to charge the EV but still utilized small periods of high load when necessary. The study main objective was to utilize coordinated charging to avoid overloading the grid and not to minimize the electrical costs of the user. Additionally, the study only dealt with electrical vehicles, ignoring other variables in the household.

The study in [9] presents a more conventional Home Energy Management System (HEMS) architecture, acting at the household appliance level but not considering energy transactions with other elements of the building such as EVs. In another example, the work presented in [10] performs appliance scheduling based on priority levels. Both studies address only solar and grid power management, not considering EVs.

More recently, several research works have focused on a more holistic approach addressing building energy management systems with EVs, Renewable Energy Sources (RES), Energy Storage Systems (ESSs) and the Grid. A model derived from the preference of the users regarding the scheduling of heterogeneus equipments is proposed in [11]. Using linear programming, this work is shown to reach the lowest cost while maintaining user comfort by employing a charging and discharging strategy for both the ESS and EV that is able to capitalize their flexibilily and increase the life of the batteries.

An electric energy management system is proposed in [12] addressing a residential neighborhood connected to the grid with electric vehicles, battery storage, and solar photovoltaic (PV) generation. This paper focuses on the energy management system designed to optimize the electricity consumption of individual households, relying on the energy demand forecast, on the EV battery status and other inputs.

The paper is organized in the following way. Section II presents the architecture of the underlying system, identifying the key components and providing insights into their operation. Section III details the baseline and proposed algorithms. Section IV documents the simulation environment while Section V presents and discusses the performance results of the algorithm in five different scenarios. Finally, Section VI concludes this paper with its key insights and prospective lines for future research.

II. Architecture

In this work we address the development of a decision algorithm aimed at minimizing the electrical bill of a house.The V2G chargers allow the algorithm to use EVs as energy storage devices (batteries) to supply energy to the house in periods of high demand. The house can also have stationary batteries that can store and provide energy with a high availability.

The goal is to build a smart agent that receives several inputs such as the connected EVs, household energy demand forecast, energy production, and so on, and take action in order to reduce the electrical bill of the house. A graphic perspective of the involved modules is depicted in Fig. 1. The actions that this agent can perform consist of energy exchanges between the available elements. The algorithm runs periodically and decides on what batteries to charge/discharge in order to satisfy the needs of the house as well of the EVs.

A. Components and Algorithm Inputs

This section presentes a more detailed description of what are the components that make up this environment and what the proposed algorithm has to deal with.

1) Household Energy Consumption Meter and Prediction: One of the inputs the decision algorithm receives is a prediction of the energy consumption of the household for the next hour. This prediction is useful since it can establish a concrete value of the overall household needs as well as give an insight on the ratio consumption versus estimated production.

The approach followed in this work adopts a generic model in the early operation days of the systems, while not enough local information is available to predict household consumption, and later switches to the household's specific model, which is trained with the real consumption values of the household, whose collection using a dedicated meter begins when the system is deployment.

2) Energy Production Meter: There are different renewable energy sources that can be installed in a house. In this work, the only form of energy production considered is photovoltaic panels. Energy production readings can be obtained typically through a physical meter (real values) or estimated using Eq. 1 that employs the solar irradiance [13].

$$E = A * r * I * p \tag{1}$$

where **E** is the energy produced in KWh, **A** is the area of the solar panel, **r** is the yield of the solar panel given by the ratio: electrical power (in kW) of one solar panel divided by the area of one panel, **I** is the solar irradiance, and **p** is the overall solar panel performance including all losses such as orientation and aging (75% is a good value). Most solar panels have a yield between 15% and 20% [14]). Irradiance can be obtained from a meter or using an API such as [15], which is free and provides *Direct Normal Irradiance* (DNI) readings in real-time.

3) Stationary Batteries: Stationary batteries are permanently connected to the house and can be used whenever the decision algorithm deems it, which makes them more useful than the battery of an EV, given its intermittent availability. Batteries have information that is relevant for the algorithm to make its decisions, namely:

- **Maximum Capacity**: Total amount of energy the battery can hold (kWh).
- **State of Charge (SoC)**: Current amount of energy the battery is holding (between 0/empty - 1/full).
- **Charge rate**: Amount of energy that can be charged/discharged per unit of time (kW).
- **Charge cost**: Cost of storing energy in a battery in the perspective of its degradation.

4) Electric Vehicles: V2G chargers allow bidirectional charging, allowing the proposed energy management system to use the energy stored in the vehicles to suppress the needs of the household. However, unlike stationary batteries, their energy cannot be fully drained, since that would impair

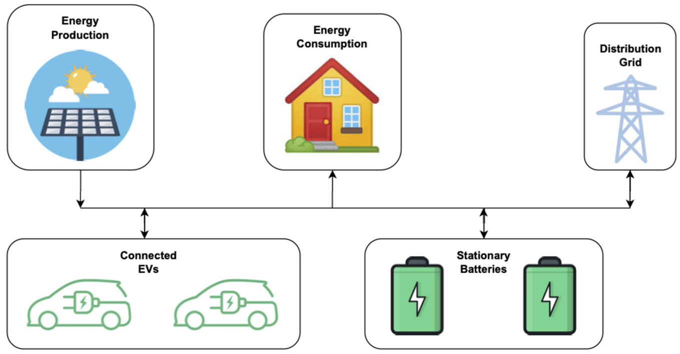

Fig. 1: Household Energy Ecosystem Components

the daily schedule of the EV's users. These variables where considered by the algorithm:

- **Battery capacity, SoC, charge/discharge rate**: Information about how much energy the EV can hold, is currently holding, and how fast it can charge/discharge.
- Energy needed for the next trip. This would work as a minimum boundary for the EV Soc. Basically, when the EV is leaving, it must contain more than the energy value estimated for the next trip.
- EV departure time. This is relative to the time the EV is going to leave. Basically, it is a deadline to fulfill the requirements of the previous item.

The responsibility of dealing with the battery of an EV should not fall upon a machine learning model, which cannot predict the EV behavior with an acceptable error. The EV behavior can be unpredictable or inconsistent, emergency trips might be necessary and the amount of energy the EV is left with should be decided by the user. To solve this, in a real-world scenario, both departure time and necessary energy could be set by the user through, e.g, a mobile application.

5) Grid: Every house is connected to the distribution grid. Unlike the energy produced by photovoltaic panels, the energy from the grid has a cost. In this project, the decision algorithm tries to minimize the electricity bill, so it needs to minimize the energy consumed from the grid. However, even when energy production is low or batteries are depleted, the energy demand in the household and in connected EVs does not stop. In this scenario the grid acts as an infinite source of energy.

III. Decision Algorithm

For each module that can receive or give energy, the decision algorithm computes how much energy it should give or receive. Every time the decision algorithm is called to take action, it creates two lists: one that contains the elements that can receive energy and the other that contains the elements that can dispense energy, both ordered by priority.

Priority levels represent how much a device "wants" to charge or discharge. For example, the work in [10] addresses a related problem and uses a similar principle. There are five levels of priority for charging and discharging, in inverted order between the two lists. Basically, 0 is the level with higher priority, and 4 is the level with less priority for discharging something. However, for charging, 4 is the level with more priority and 0 is the level with less priority. A device with D discharge priority only gives energy to an item with C charge priority if $D \leq C$, as can be seen in Fig. 2. The only purpose of having the priority values reversed is to facilitate the decision rule.

The elements in the two lists are eligible to charge or discharge. Being in the list does not mean that the object will necessarily charge or discharge. In fact, the same EV or battery may appear in both lists, since they are eligible to charge or discharge (a battery that is not full can charge or discharge). Whether they are selected to do one thing or the other depends on the environment.

A. Elements Eligible to Supply Energy

1) Photovoltaic Panels: The only element that receives the highest discharge priority score (0) are solar photovoltaic panels, as the energy being produced must flow somewhere immediately, even if it means giving it away for free to the grid.

2) Electrical Vehicles: have a user defined parameter that sets the minimum value of charge that the EV must hold. If the current SoC is below this level, the EV is considered unavailable to provide energy. On the contrary, if the electric vehicle contains enough energy, it is available to provide energy to the house or to other batteries. In case the EV will be parked for a long time, it receives a priority of 3, meaning that it can provide energy if necessary. If the EV will leave soon, it receives a priority of 2, meaning they will provide energy before EVs that will stay parked. This is because the EV is seen as a source of energy that would soon be unavailable. Also, priority level 2 specifically allows the stationary batteries to receive energy from the EV in question, in case the algorithm senses that the household will have a deficit of energy in the short term. In both scenarios, the amount of energy the EV is willing to discharge is the difference between the current SoC and the user-defined energy needs for the next trip, provided that the SoC is higher than the threshold. This ensures that the EV never goes below this limit.

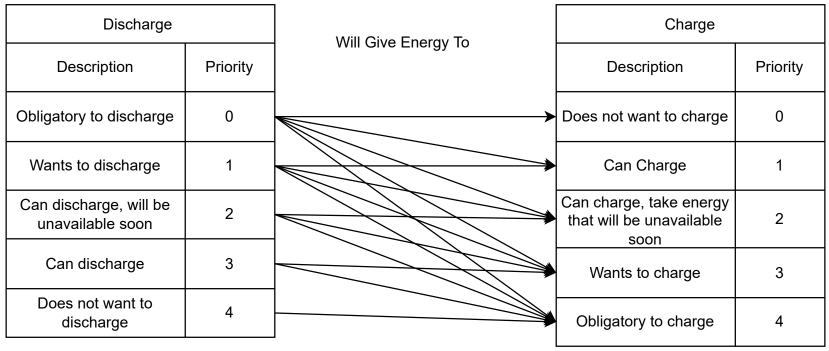

Fig. 2: Decision algorithm Priorities

3) Stationary Batteries: have typically a priority level of 3, indicating that their energy is only spent on items that highly require it. In this case, all the stored energy is available to be provided. However, if the production of energy is currently higher than the household consumption prediction and the available space in the connected batteries and EVs is not enough to store the predicted remainder of energy, the battery's priority is set to 1, in order to empty the battery by making its energy more accessible. This is done to create space for the energy that is produced.

4) The Grid: has an "*unlimited*" supply of energy and can provide energy to the household depending on the current price or the demand of the household. Batteries have an expected life spans that depends on how much they are used, since they deteriorate with use over time. From these variables, it is possible to define a cost to charge a battery.

B. Elements Eligible to Consume Energy

1) Household: One way of providing energy to the household is discharging one or more EV or stationary batteries at a rate that satisfies the household needs. In this paper, we assume that the amount of energy required by the house is predicted using a machine learning model. This model has been developed and evaluated by the authors in another work, which is outside the scope of this paper. The prediction is used to estimate the ideal rate for discharge of EVs and/or stationary batteries. However, any such predition will have errors. If the prediction is too high, some of the energy being discharged is not used and flows to the grid for free, being "lost". If the guess is too low, the remaining household needs are automatically suppressed by the distribution grid, potentially increasing user costs.

The algorithm collects information on how much energy is available, how much is needed in the next time step, and how much will be produced in the solar panels. With these parameters, as well as the price of the energy of the grid, it decides how much energy to reserve for the household. If the algorithm realizes there is no available energy in the batteries, it decides to set the household to (receive) priority 0 (i.e., only receives energy from the solar panels). However, most of the times this just means that the distribution grid will supply the household. In a scenario where an excess of energy is available (being produced or stored) or the grid price is too high, the algorithm uses the energy prediction value with the highest priority, not afraid of wasting energy. However, if there is not much energy available and the grid price is acceptable, the algorithm considers not trusting the prediction as much and reserves only a fraction of it, as it will have an error and could translate in energy loss. The algorithm also considers that there might be an error in the energy production prediction, making sure that the energy being produced is always directed to the household before going to the grid.

2) Electrical Vehicles: must have a SoC value higher than the user-defined threshold. If this is not the case, the EV is given a high priority to charge. Utilizing the estimated departure time, energy needed, and charge rate, the model can decide if the charging action needs to start as soon as possible or if it can wait. If the charging action needs to start right away, the EV receives a priority value of 4 (mandatory), if not, a priority value of 3 is given, which is still a high priority. The amount of energy that the EV will charge is the amount needed to reach the threshold. After the minimum energy requirements are satisfied, the EV receives a priority of 1, only receiving energy if there is an exceeding amount somewhere.

3) Stationary Batteries: typically have a priority of 1. This means that they store energy from the solar panels that exceeded the current household and EV needs. Batteries can also store energy from the grid when its cost is low. If the consumption (prediction) is higher than the production, the algorithm looks at the available energy in stationary batteries and vehicles. If the energy stored is not enough to satisfy the house needs in the next time steps, the battery priority is increased to receive energy. This way, the battery is eligible to receive energy from EVs that are leaving soon (and thus are not available in the next time steps to help satisfy household consumption). Additionally, it increases the chances of the battery to receive energy from the grid, in case the price of the grid is lower than average.

4) The Grid: is capable of receiving excess energy in the household. Because this is not a desired result, the grid is given a priority level of 0 to receive energy. There are plenty of ways of using the exceeding energy. For example, in a more realistic scenario, this energy could be used to run appliance jobs, such as washing clothes, or store energy in the form of heat/cold in the building.

C. Baseline Decision Algorithm

A baseline decision algorithm was also built to provide a term for comparison. This algorithm privileges the use of the energy produced by photovoltaic panels to supply household loads and charge EVs or stationary batteries. In this regard, it always charges the EVs when they are connected, until they are filled, even if that requires utilizing energy from the grid. Additionally, in this algorithm, electric vehicles do not engage in discharging actions, meaning that they do not make use of bidirectional chargers. The stationary battery is used solely to store excess energy from the solar panels. However, it can still provide energy to the house or EVs.

IV. Simulation

The decision algorithm was tested in a simulated environment, provided that it enables an easy exploration and evaluation of multiple scenarios.

A. Components

The identified components were implemented in Python classes. This section provides an overview of how such modules operate.

1) Consumption Meter: The consumption readings are loaded from a CSV file. The used dataset [16] contains household consumption reading for London houses. The simulation iterated through the file and for each time step read the next consumption value.

2) Production Meter: The irradiance values required to calculate the energy production were also loaded from a CSV file obtained from [15]. This file contains irradiance readings from London (the same location as the consumption dataset), and it matches the time intervals. The simulation iterated through the file and, for each time step, read the next irradiance value. This value is used to calculate the total energy production in that time step, according to Equation 1.

3) Batteries: Batteries were implemented in a simple class. This class was used for stationary batteries and EV batteries. Batteries have a maximum capacity, current capacity and charge rate. Additionally, the price and battery cycles were also implemented as variables to calculate the battery charge price. Losses in the charging and discharging process are also considered.

4) EVs: Both departure time and necessary energy will provided by the user through a mobile application. In the simulation environment proposed to test the algorithm, several trips are randomly simulated.Upon the start of the simulation, the number of EVs/V2G chargers used by the household family is selected. Every hour, for every free charger that is not occupied, a probability is established that an EV will arrive and take that space. This probability is 10% at every hour except in the hours: 11-13, 18-20, and 22-23. These hours were defined as the most common hours for an EV to arrive and the probability of an EV arriving is boosted to 25%.

When the EV arrives, its SoC is determined by the SoC with which the vehicle left, the previously user defined threshold (energy needed for the trip), and a random value representing how much of the threshold value was actually used, according to Equation 2:

$$SoC = Prev.SoC - Prev.Threshold * used \qquad (2)$$

where *used* is a value between 0.2 and 0.8. This value represents the percentage of the value that was predicted to be needed that was actually used. The electric vehicle never has an SoC greater than one or fewer than zero. If this is the first time the EV is introduced, the SoC value is set to 0. The minimum battery threshold represents how much energy the EV will need in the next trip and was defined with triangular probability. This distribution allows us to specify a minimum, maximum and most common value or mode. On this instance, the minimum value is 0.1, maximum is 0.8 and mode is 0.3.

After arriving, the departure time is immediately calculated. The hours that were considered more common to leave the house were 8, 14 and 20. The simulation generates the actual departure time with a Gaussian distribution, considering the mean on the selected value and a deviation of 2 hours. If the resulting hour is lower than the current hour, the EV only leaves the next day. The departure and arrival time behavior of an EV according to the simulation can be seen in Fig. 3. At each hour the line depicts the probability of an EV being parked at home. As it can be seen, the probability of the vehicle being at home decreases in the morning, afternoon and around dinner time. This probability is higher at nigh, lunch time and evening.

5) The Grid: was modeled to account for two different pricing possibilities: linear price of 20 cents per kWh, and variable price that fluctuates between 5 cents and 35 cents, with average value of 20 cents per kWh. The period with the lowest price is around 4 to 5 a.m., when the energy usage is the lowest. The period with highest price is around 5 p.m., when demand is higher. We considered that this pattern has a daily periodicity corresponding to Equation 3, resembling a real-world scenario [17].

$$price = 0.15 * (cos((hour/3.82) - 10.5) + 1) + 0.05 \qquad (3)$$

where price is the price of the kWh in euros and the current hour is the hour of the day.

V. Evaluation

In this section, the proposed decision algorithm is tested and compared to the baseline defined in Section III-C using the described simulation environment. Several parameters are modified to test the algorithm under different conditions.

A. Scenarios

Several scenarios were planned to explore variations in the testing environment and highlight the strengths and weaknesses of the algorithm. Table I summarizes the constant parameters considered for all tests.

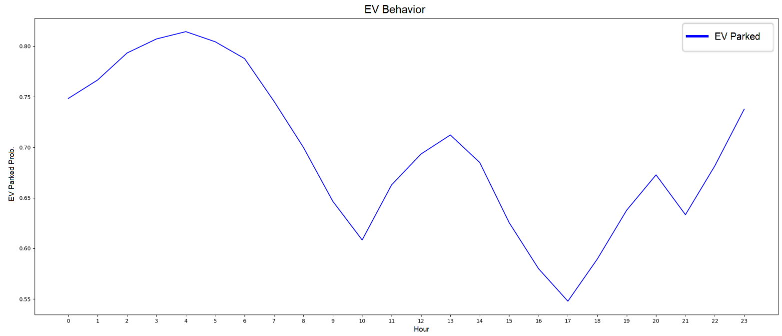

Fig. 3: Probability of an EV being parked per hour of the day

Constants	Value
Battery charge/discharge energy loss	2%
EV battery max capacity	24 kWh
EV battery charge rate	3 kW
EV battery price	4500 €
EV battery price per kWh	0.038 €
Stationary battery max capacity	50 kWh
Stationary battery charge rate	5 kW
Stationary battery price	10000 €
Stationary battery price per kWh	0.04 €

TABLE I: Values kept constant through the experiment.

A base scenario is considered where the average monthly value of production is typically smaller than the consumption of the household. The household is assumed to have 2 EVs (V2G chargers), 1 stationary Battery and a dynamic Grid behavior concerning the cost of energy. Following this base scenario, four variations are considered: 1) having only 1 EV, 2) having 3 EVs, 3) having no stationary batteries and 4) having a linear grid price behaviour.

B. Results and Discussion

This section presents the obtained results. A total of 10 test households, with different house consumption behaviors, were randomly picked from the consumption meter dataset [16], and simulated under the five identified scenarios (base plus four variations).

Since the proposed decision algorithm aims to minimize the electric bill cost, in order to evaluate the performance of the algorithms, a metric named "Total cost" should be defined. .Furthermore, besides the payment of energy to the Grid, the battery depreciation cost needs to be accounted for. In our model we assumed a fixed value per kW charged as documented in Table I. The "Total cost" is the sum of the Electric Bill Cost and the Battery Depreciation Cost.

Fig. 4 depicts a plot of the monthly average "Total cost" in these 10 houses. The continuous lines are relative to the proposed algorithm, while the dotted ones represent the baseline decision algorithm. The black and thicker lines are relative to the base scenarios, while thinner ones pertain to its variations (1-red, 2-orange, 3-green, and 4-blue).

The first impression is that the dotted lines are generally above the continuous lines for the same scenario, which means that the designed algorithm performs better than the baseline. On variation 1 (red), one less EV relies on the system to charge. Therefore, it is expected that the total cost is less than the base scenario (black). In contrast, in variation 2 due to the increase in the number of electric vehicles to three, the total cost increases.

In variation 3 the stationary battery is removed, making it unavailable to store energy in. The total cost of the proposed algorithm is significantly reduced when compared to the baseline, leveraging on the use of the V2G chargers to handle the EVs as batteries and use their energy to supply the household, something that the baseline algorithm cannot.

Variation 4 is where the performance difference between the baseline and the proposed algorithm is smaller. In this scenario, the price of the grid exhibits a linear behavior. One thing to notice is that on the proposed algorithm (continuous blue and black lines), even though the grid price has the same average price over the day, the proposed model can make use of the low price periods to produce savings. However, the baseline algorithm (dotted blue and black lines) has the black line higher than the blue line, which means that it "prefers" the flat price. This happens because the time when the grid energy is higher coincides with a period of high house consumption (5 p.m.), since the grid is more saturated at that time. So, the baseline algorithm is buying energy in periods of high price and not benefiting from the low energy price (around 4 a.m.) to charge batteries.

Table II documents the average annual Total Cost by scenario and decision algorithm. As shown, the maximum savings (33.24%) occur for variation 3 when there is no stationary battery and the proposed algorithm can still manage the EVs batteries to balance the energy in the household. The proposed algorithm was also able to provide significant cost gains relative to the baseline in the remaining scenarios (20.06%, 15.38%, and 22.42 %, respectively, for the baseline and variations 1 and 2), with the exception of variation 4, where the difference can be considered negligible, albeit ensuring a baseline improvement of 3.44%.

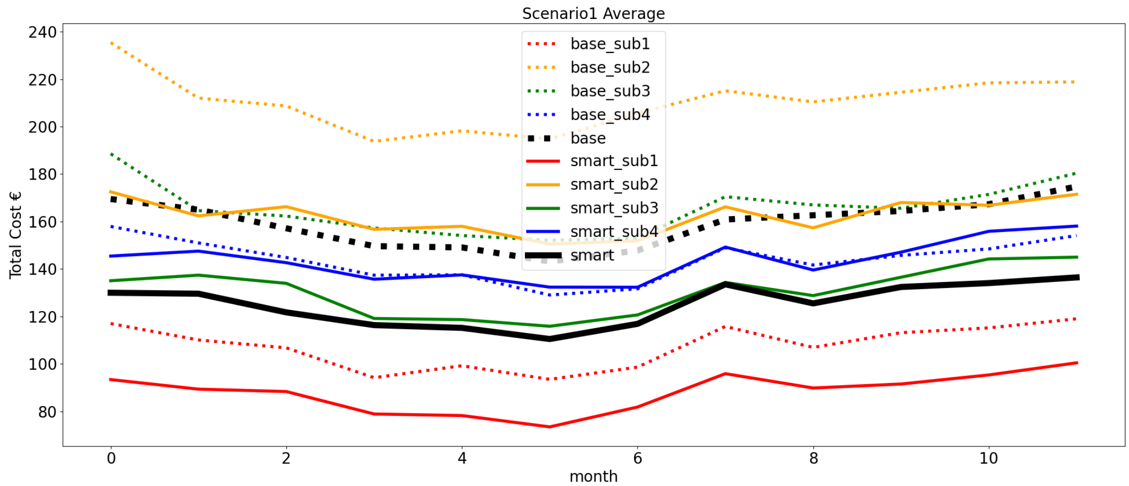

Fig. 4: 10 Test Houses Average Total Cost

	Total Cost (€)		
Scenario	Baseline	Proposed	Savings (%)
Base	1423.70	1138.05	20.06
1	896.69	758.74	15.38
2	1968.00	1526.64	22.42
3	1821.73	1216.15	33.24
4	1340.43	1294.37	3.44

TABLE II: House Average Annual Total Cost by scenario and Decision Algorithm

VI. Conclusion

This paper proposed the development of a decision algorithm envisaging lowering the electrical bill costs of a house connected to the Grid that also encompasses photovoltaic generation, stationary battery energy storage, and electric vehicles with bidirectional charging/discharging capabilities.

The proposed decision algorithm was described with focus on the two types of participating elements: those of supply energy and those who consume it. In order to assess the performance of the algorithm a simulation environment was developed. This simulation environment employs realistic data sources, bringing the results closer to what would happen in a physical deployment.

The proposed approach was shown to perform better than a baseline algorithm, built for comparison purposes. The designed method and the baseline were compared in a series of scenarios and in different test houses. For the different scenarios, the worst amount of savings achieved by the proposed approach was a price reduction of 3.44%, showing that the algorithm will achieve marginal savings in a situation where the grid has a linear price behavior and the production is lower than the demand. The best result was a cost reduction of 33.24% that achieved when the household had no stationary battery to rely on. The average result of the proposed algorithm, across all sub-scenarios and test houses, was a 18.9% cost reduction, comparing to the baseline.

Future work includes exploring different variations of the energy balance (production/consumption) and of the cost variation in the main grid, possibly using forecasting information. Another improvement to consider is making the simulation more realistic by shortening the algorithm's run interval from 1h to a few minutes, potentially reducing the impact imprecise load demand forecasts.

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