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Optimized Management of Solar Energy Surplus for Electric Vehicle Charging in Urban Residential Areas

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Electric Vehicle, Photovoltaic Energy, Energy Management System, PV Self-Consumption, Taguchi Method.

ABSTRACT

The rapid urbanisation of the population has led to challenges such as increased energy demand, higher building sector activity, and a need for infrastructure development to accommodate rising transportation needs. At the same time, the global shift toward sustainable energy has prompted many households to adopt photovoltaic (PV) systems for self-consumption, using solar panels to meet daily energy needs. This often leads to surplus energy being returned to the grid, leading to suboptimal resource use. Meanwhile, the adoption of electric vehicles (EVs) has surged due to their environmental benefits, such as reduced greenhouse gas emissions. However, the growing number of EVs demands new infrastructure to meet their charging needs. This study proposes a solution to optimize the use of surplus energy generated by residential PV systems in urban neighbourhoods to power an electric vehicle charging point. The excess energy is first used to charge energy storage systems (ESS) until they reach an optimal state of charge (SOC), as determined using the Taguchi method. An energy management strategy (EMS) is also introduced to regulate energy flow efficiently, addressing the intermittency of solar power production. This approach ensures that energy from residential solar producers is utilized effectively for EV charging while improving overall energy management within the neighbourhood. By optimizing energy use in this way, the study offers a practical solution for integrating renewable energy and supporting the growing demand for EV infrastructure in urban settings.

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إدارة مثلى لفائض الطاقة الشمسية لشحن المركبات الكهربائية في المناطق السكنية الحضرية

أمال نفراوي، خالد قندوسي، ربيع العثماني، عبد الرحيم بوطاهر

ملخص: أدى النمو السريع للتركيبة السكانية الحضرية إلى ظهور العديد من التحديات، بما في ذلك التوسع في قطاع العمران، وزيادة استهلاك الطاقة، وضرورة النمو الهيكلي للإنتاجية، ورفع مستويات المعيشة. كما أدى هذا التوسع الحضري المتزايد إلى زيادة نشاط النقل، مما يتطلب تطوير البنية التحتية المناسبة. كما يشهد قطاع الطاقة العالمي في الوقت نفسه تحولا كبيراً نحو الاستدامة. واستجابةً لهذا التحول في مجال الطاقة، يتجه المواطنون بشكل متزايد إلى الاستهلاك الذاتي للطاقة الكهروضوئية كوسيلة لتلبية احتياجاتهم اليومية من الطاقة، وذلك من خلال تسخير طاقة الألواح الشمسية المثبتة على أسطح المنازل. ومع ذلك، يمثل هذا النهج تحديًا فريدًا من نوعه، حيث يتم تسليم فوائض الطاقة إلى موردي الطاقة، مما يؤدي إلى عدم كفاءة استخدام الموارد. وفي الوقت نفسه، اكتسب اعتماد السيارات الكهربائية (EVs) زخماً ملحوظاً بسبب مزاياها البيئية الملحوظة، مما يساهم في تقليل انبعاثات غازات الاحتباس الحراري. ومع ذلك، فقد استلزم الدمج الواسع النطاق للمركبات الكهربائية إجراء تحسينات في البنية التحتية لاستيعاب احتياجات شحنها. في هذا العمل، نقترح حلاً لاستغلال فائض الطاقة التي ينتجها منتجو الطاقة الشمسية المنزلية في إحدى المناطق، كمثال، لتزويد نقطة شحن للسيارات الكهربائية (EVs)، بعد شحن أنظمة تخزين الطاقة حتى الوصول إلى حالة معينة من الشحن الأمثل، ويتم تحليل هذه الأخيرة باستخدام طريقة تاغوتشي. كما تم اقتراح استراتيجية لإدارة الطاقة (EMS) من أجل مراقبة جيدة للطاقة لمعالجة حالات تقطع الألواح الكهروضوئية.

الكلمات المفتاحية: المركبات الكهربائية، الطاقة الكهروضوئية، نظام إدارة الطاقة، الاستهلاك الذاتي للطاقة الكهروضوئية، طريقة تاغوتشي.

1. INTRODUCTION:

As the global concern for climate change grows, the imperative need to reduce greenhouse gas emissions and transition towards cleaner energy sources has become increasingly evident. Among renewable energy technologies, photovoltaic (PV) systems have emerged as a promising and sustainable solution, playing a pivotal role in mitigating carbon emissions and fostering a more environmentally conscious energy landscape [1]. On the other hand, the rapid urban demographic growth has spurred numerous challenges, including expansion of the building sector, rising energy consumption, increased infrastructure needs, and higher living standards. This surge in urbanization has also catalysed heightened transport activity, necessitating suitable infrastructure development. Simultaneously, there is a notable shift occurring in the global energy environment toward a more sustainable trajectory. In light of this transition in energy sources, individuals have progressively embraced the practice of photovoltaic (PV) self-consumption as a strategy to fulfil their daily energy requirements, utilising the potential of solar panels that are installed on the rooftops of residential buildings. The remarkable aspects of PV technology include its adaptability to residential settings, ease of installation and low maintenance [2], [3].

However, the surplus energy often occurs because PV panels continue to generate electricity during the day when consumption is low. This energy can be invaluable during peak demand hours, typically in the evenings and nights, thus alleviating the stress on conventional power sources. One of the notable characteristics of PV systems is their ability to inject surplus energy into the grid. Often, the excess energy generated is routinely delivered back to energy suppliers, resulting in suboptimal resource utilization. Alternatively, the energy can be stored in the energy storage systems (ESS), making it available for use during peak demand periods or when solar generation is reduced, such as at night or during cloudy days [4].

It is important to note that the adoption of storage systems is not universal, and not all residential PV installations include them. Moreover, even when storage systems are present, their capacity may sometimes be insufficient to store all surplus production, potentially leaving some excess energy unused. On the other hand, the lifestyle of occupants in residential areas is a critical factor in determining the effectiveness of PV integration. Their energy consumption patterns, including when and how much energy they use, greatly influence the potential for PV surplus injection into the grid.

Regarding the transportation sector, electric vehicles (EVs) are a crucial component of this transition, offering significant benefits in terms of reducing greenhouse gas emissions and dependence on fossil fuels [5]. Thus, to encourage their integration and motivate EV owners to undertake extended journeys, it is important to expand the public charging infrastructure. The provision of public charging infrastructure in residential areas provides increased accessibility and convenience for EV owners who do not have access to a personal parking place or garage to install a private charging point. This is particularly relevant for those living in apartment complexes. For EV drivers residing in urban areas, the presence of charging stations in various neighbourhoods is a welcome development, particularly when they are located at a considerable distance from a charging facility.

In addition, EV usage is highest during the day, particularly from 8 AM to 6 PM, which corresponds to typical commuting hours. Consequently, the demand for EV charging is extensive during this period. Aligning the surplus PV energy generated during the day (typically between 7 AM and 5 PM, when sunlight is abundant) with the high charging demand of EVs presents a significant opportunity for optimizing energy use[6].

In addition, the extensive utilisation of self-consumption PV generation holds significant potential. Moreover, there is a variation in electricity use among households, resulting in diverse load profiles. Furthermore, it should be noted that not all users will engage in simultaneous charging of their vehicles, owing to the likelihood of varying transportation needs, nor will their energy consumption patterns be uniform throughout the day.

This alignment presents a significant opportunity for optimizing energy use. The surplus PV energy generated during the day, when household consumption is low, can be harnessed to meet the high charging demand of EVs. Implementing smart charging strategies that prioritize EV charging during peak PV production hours would enhance the efficiency of PV energy utilization, reduce reliance on the grid, and contribute to the overall stability and sustainability of the energy system.

Another key factor is the trend of increasing residential electricity prices coupled with decreasing battery storage costs. Consequently, charging EVs using the surplus PV energy, rather than injecting it into the grid, is more advantageous. This approach allows for the subsequent utilization of stored energy in vehicle-to-grid (V2G) technology, enhancing energy efficiency and sustainability[7], [8].

For instance, in this study, we propose an innovative strategy that seamlessly integrates these various aspects of urban life. Our goal is to harness the surplus energy produced by household solar systems within a typical urban district to power an EV charging point. This approach effectively bridges the gap between renewable energy surplus and the increasing demand for EV charging infrastructure. Additionally, we implement an energy management strategy (EMS) to efficiently monitor and manage energy usage in response to the intermittent nature of PV panel output.

2. METHODS:

To comprehensively assess the dynamics of EV charging in a residential area and its interaction with PV systems, a representative simulation model was developed. This model simulates a fictitious residential neighbourhood and an EV connected to a recharging point.

2.1 Household neighbourhood

The residential neighbourhood considered consists of five distinct houses, each designed to have identical PV characteristics, including panel type, orientation, and tilt angle. This uniformity eliminates structural or installation disparities, ensuring that variations in energy generation and consumption are primarily attributed to the individual household's demands throughout the day. Throughout the simulation, meteorological conditions, such as solar irradiance and temperature (1000W/m² and 25°C, respectively), are held constant to eliminate external environmental variables that might affect PV generation. Each house's data on both energy consumption and PV generation within the neighbourhood is determined to enable tracking the energy flows within the neighbourhood, facilitating the development of the EMS. This control allows for a focused evaluation of the impact of varying household energy demands on EV charging decisions. To introduce variability into the simulation, each house is assigned a unique daily energy consumption profile. These profiles represent the differing energy demands of households within the neighbourhood, influenced by factors such as the number of occupants, their daily routines, and the use of energy-efficient appliances and materials. They also reflect realistic usage patterns and peak demands, capturing the random nature of consumption exhibited by household users. The tool suggested in reference [9] is utilized to model the stochastic behaviour based on real-world data. To introduce randomness into the process, a collection of daily load profiles has been developed for each occupancy level (namely, low occupancy households), encompassing buildings of modest to moderate size. These profiles were derived using randomly selected consumption patterns observed during the winter period, when demand tends to be higher. Each house has its own ESS and is connected to the electrical grid, serving as a backup source of electricity when PV generation is insufficient to meet household demand. This connection enables seamless transitions between local PV-generated power and grid-supplied electricity, ensuring uninterrupted energy supply.

The PV generation at time (t) can be written as in equation (1)[10]:

$$P_{PV,t} = \eta_{inverter} * \eta_{PV} * I_t * A \qquad (1)$$

Where: $\eta_{inverter}$, η_{PV} are the inverter efficiency and the PV cell efficiency, respectively, I_t is the incident solar irradiance on the tilted place at time t (W/m²) and A is the PV area (m²).

2.2 Electric vehicle charging point

The EV is modelled using a lithium-ion battery model (LiB) due to our central emphasis on the charging process during its stationary state at the charging point. This choice is also justified by its widespread adoption in the EV sector, owing to favourable attributes such as high energy density, robust power capabilities, nominal voltage, and capacity for numerous charge and discharge cycles[11]. The electrical equivalent circuit model of the battery considered in this study is the Thevenin model, known for its simplicity and good accuracy[12]. The daily EV energy demand (E_{EV}) for charging is defined as [10].

$$E_{EV} = \eta . D \tag{2}$$

Where D is the daily driving distance, considered in this study 160 Km, which is close to serving the range requirements of personal drivers [13], [14]. And η represents the energy consumption rate of EVs (measured in kWh/km), which is influenced by several factors, including ambient temperature, driving style, and vehicle application. EVs tend to consume more energy during extreme weather conditions (both cold and hot) compared to milder periods of the year. This increased consumption is largely due to the need for climate control within the vehicle, as maintaining passenger comfort through heating in cold weather or cooling in hot weather demands additional energy. Consequently, the seasonal energy needs of EVs are significantly affected by fluctuations in air temperature.

At the arrival of the EV to the charging point, the state of charge (SOC) is estimated and is supervised to ensure good protection to the battery from over charge. The SOC is defined as the ratio between the remaining capacity and the initial capacity value of the battery, as expressed in the following equation[15].

$$SOC = \frac{Remaining\ capacity}{Rated\ capacity} \tag{3}$$

The EV is connected to both individual houses and to the electrical grid, without factoring in the vehicle-to-grid (V2G) mode, in this study. Upon the commencement of the charging process, the SOC is assessed, and its progression is closely monitored until the battery reaches its maximum charge capacity. The charging procedure is carefully regulated to ensure that the SOC remains within the necessary operational range, in order to mitigate potential detrimental effects on battery health and longevity. Thus, the battery is protected from overcharge and deep discharge following limits (SOCmin and SOCmax)[16].

2.3 Simulation and algorithm

Table 1 lists the PV parameters of the panel considered in this simulation, which were taken from the Matlab/Simulink library. The panel has a maximum power of 218.871 W.

Table 1. PV panel properties.

Module	1Soltech 1STH-220-P
Maximum Power (W)	218.871
Open circuit voltage (V)	36.6
Short circuit current (A)	7.97
Voltage at maximum power point (V)	29.3
Current at maximum power point (A)	7.47

The PV array is connected to a DC/DC boost converter to elevate the PV voltage while tracking the maximum power point of the PV array using the Perturb and Observe maximum power point tracking algorithm (P&O MPPT) to monitor the maximum power output by the PV array and adjust the duty cycle. The effectiveness of the P&O MPPT's tracking and the ease with which it can be implemented have led to its widespread adoption in a variety of grid-connected inverters and charge controllers for small and medium-sized commercial solar PV systems[17].

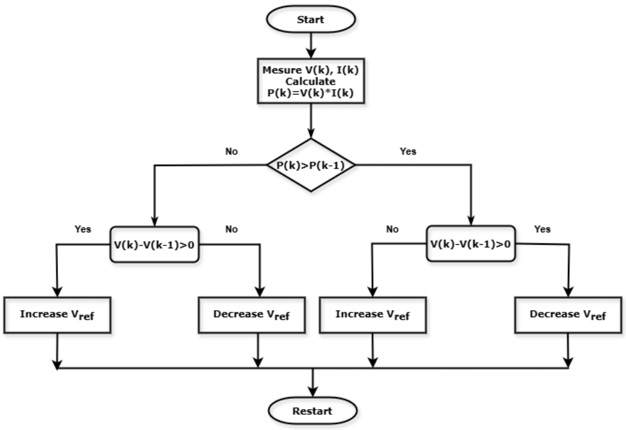

Figure 1. The flow chart of Perturb & Observe maximum power point tracking algorithm.

One of the PV constraints is its intermittent production caused by environmental conditions, such as the low or complete absence of solar irradiation, especially during night time. To solve this issue, the energy storage system (ESS) is required to submit the peak period' need. In this work, we consider the lithium-ion battery to stock the surplus energy produced during the day, in purpose of improving the quality and the reliability of power stations. The LiB ESS is connected to the PV plant via a half bridge bidirectional DC/DC converter. However, the existence of the ESS remains inadequate in addressing the comprehensive requirements of all inhabitants. Due to this rationale, the electrical grid is crucial for supplying power to buildings. Consequently, the residential property is connected to a single-phase electrical grid through an LCL filter, operating at 50Hz frequency. A single phase full-bridge inverter interfaces the system with grid [18], [19]. The inverter control is used to balance the active and reactive power exchanged with the grid, based on sinusoidal pulse-width modulation (PWM) using dq-frame control under unbalanced conditions[20], [21]. Therefore, Figure 2 describes the circuit representing the proposed district of five houses having PV self-production connected to an EV charging point.

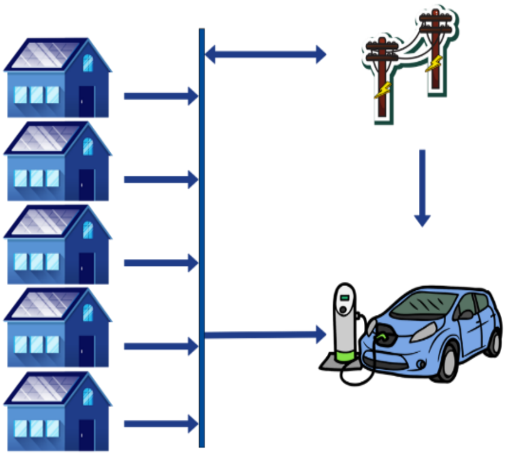

Figure 2. Proposed scheme of household PV self-production connected to the EV charging point.

In this simulation, the sizing of the PV plant and ESS was conducted, based on the specific energy demands of each house. This approach accurately represents the inherent disparities in electricity consumption among different homes. Furthermore, the SOC of each ESS is also varied from one house to another, reflecting the unique energy storage needs and conditions of each residence, as described in Table 2. The EV LiB is initialised with a starting SOC of 43%, mirroring an example of the typical SOC level of EVs when they arrive at charging points.

Table 2. System parameters.

House	House energy demand	Number of panels	PV max power	Initial SOC of the ESS
House 1	5 kWh	6 panels	1.3 kW	75%
House 2	4 kWh	5 panels	1.05kW	80%
House 3	3 kWh	4 panels	800 W	60%
House 4	2.5 kWh	3 panels	630 W	90%
House 5	6 kWh	8 panels	1.8 kW	78%

In this work, we propose an energy management strategy to control the different components of this suggested charging point in the district, following the flowchart shown in Figure 3. It should be noted that the functionality of this algorithm depends on the connection of the EV battery pack to the charging port. The EV is afterwards supplied largely by the residential PV system when the PV power output (PPVn) exceeds the power requirements of the building (PLoadn) and when the SOCESSn is over SOCmax. The aforementioned condition holds significant value for every residential property, which is why the use of the n note is employed. If the initial house does not meet the specified criteria, the controller will proceed to the next house, and so on. In cases where the SOCESS falls below SOCmax value, the PV plant associated with it will be activated and the controller will disconnect it from the charging point. Otherwise, the EV is recharged using electricity sourced from the electric grid. However, when the EV is not plugged in the charging point and PPV is higher than the house's energy demand, the controller chooses whether to inject the surplus into the grid or to charge the ESS based on its SOC.

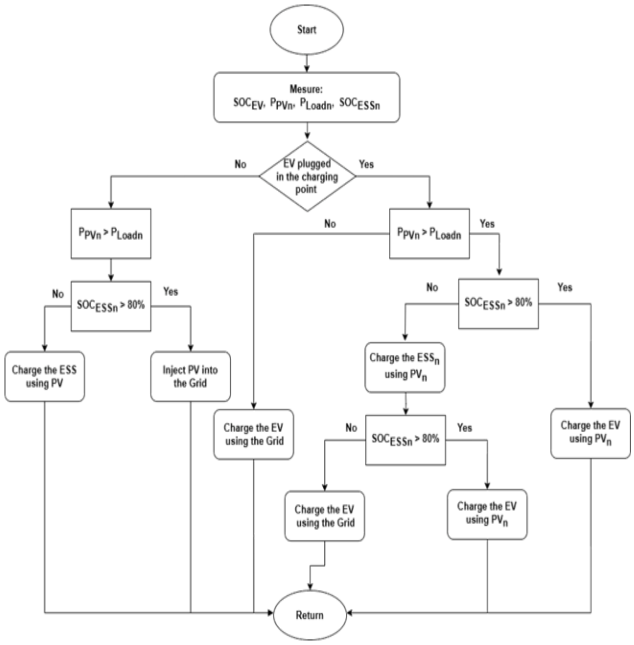

Figure 3. Energy management algorithm flowchart.

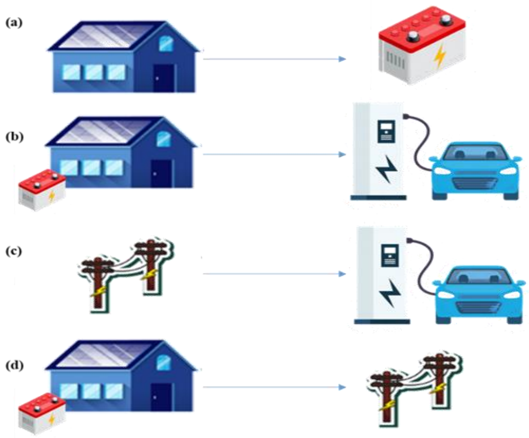

Figure 4. Different possible scenarios.

3. RESULTS AND DISCUSSION:

In order to optimize the longevity and operational efficiency of the ESS, a configuration was implemented to limit the SOC to a maximum of 80%. This measure aims to maintain its overall health. When the SOC decreases to a level below the specified threshold and the energy consumption of the house is lower than the PV generation, the house disengages from the charging point, and the injection process reverts back to the standard mode. This implies that the excess PV energy is employed to supply electricity to the household load and recharge the ESS until it reaches 80%. As a result, residences 1 and 3 were disengaged from the charging station, and their ESS were recharged using excess energy provided by the PV facilities. House 2, which had an initial SOC of 80%, effectively employed the excess PV energy to supply power to the electrical demand and facilitate the charging process of the EV. House 5 commenced its operation with an initial SOC of 78%. Subsequently, it ceased sending energy to the charging point when the ESS reached the threshold of 80% SOC. At this juncture, house 5 was reconnected to the charging point. This strategy guarantees that the priority need of meeting the house load and ESS is fulfilled.

Figure 6 depicts the charging profile of the EV battery, wherein it commences charging with an initial SOC of 43% upon reaching the charging station. The profile is segmented into four distinct times, and it is of significance to acknowledge that two residences were disconnected from the charging station due to their failure to comply with the EMS prerequisites. The EV battery was subsequently charged utilising the power supply from residential units 2 and 4, in addition to electricity sourced from the grid, throughout the time interval of 0 to 61 seconds. Then, house 5 was utilised throughout the duration of the remaining simulation period, thereby exemplifying the efficacy of the employed technique in the process of charging the battery. The variability in charging times observed in this profile can be related to discrepancies in the power values of individual residential PV systems.

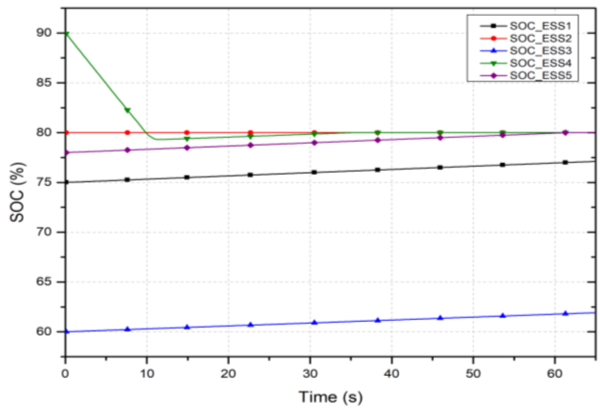

Figure 5. The state of charge of the energy storage system for the five houses.

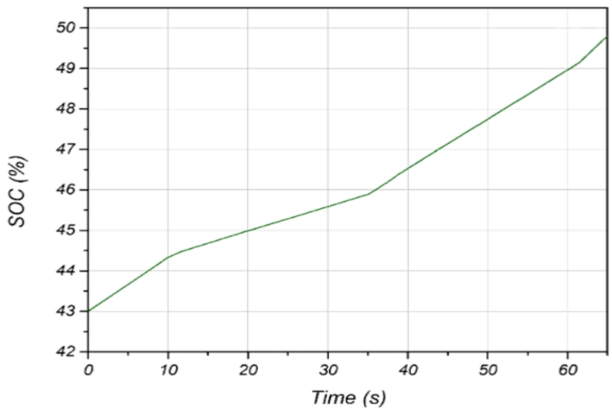

Figure 6. The electric vehicle state of charge profile.

In the context of utilizing ESS within residential settings, achieving a 100% SOC is deemed most beneficial for meeting the occupants' needs. However, to ensure the battery's health and longevity, an 80% SOC has been identified as the optimal charging threshold[22]. Additionally, to determine the ideal SOC for both the charging point requirements and the building's needs, assigning equal priority to both, we used the Taguchi method. This strategic approach enables us to optimize the energy distribution system, ensuring that both the buildings and EVs connected to our system meet their energy needs efficiently and sustainably.

The determination of the optimal charge limit for the ESS is influenced by several factors. These include the time necessary to fully charge an EV, the collective energy demand of the buildings (classified as low, medium, or high sized buildings, though for our simulations, we assumed a variable energy requirement during the winter for small to moderate building size), and the total number of buildings linked to the system. To effectively manage this scenario of energy supply, it is imperative to carefully set the charge threshold for the ESS, taking these variables into account.

In analyzing the limit SOC of the storage systems against the charging period, a structured approach is taken. The analysis involves examining short, medium, and long charging times against various ESS SOC, ranging from 50% to 100%. To select the appropriate orthogonal array (OA) design is crucial for the outcome of an experiment and relies on the total degrees of freedom (DOF) needed to analyze the primary and interaction effects, the objective of the experiment, available resources and time limitations. Orthogonal arrays enable the calculation of main and interaction effects with a minimal number of experimental trials [23]. The total DOF, must be less than or equal to the number of runs in the fixed set of orthogonal arrays (OAs)[24]. It can be calculated using the following equation, where L_a, L_b, L_c represents the number of levels of the respective factors A, B and C, respectively.

$$DOF = 1 + [(L_a - 1) + (L_b - 1) + \cdots] + [(L_a - 1) * (L_b - 1) + (L_b - 1) * (L_c - 1) * \ldots] \tag{4}$$

The degree of freedom (DOF) is then calculated to be 18, leading to the selection of an L_{18} ($6^1 3^1$) orthogonal array for the Taguchi method. This structured plan includes two factors across 18 trials to test our hypotheses. The null hypothesis posits that all means are equal, while the alternative suggests variations exist among them. A significance threshold of $\alpha = 0.05$ is set, assuming equal variances for the analysis.

In our analysis, the pooled standard deviation was found to be 3.88240, with each level of the experimental factors tested three times. Notably, as the SOC level of the ESS increases, both the mean and standard deviation values exhibit a downward trend. This pattern suggests an inverse relationship between the SOC of the ESS and the response, which in this context is the SOC of the EV. Essentially, as the ESS's SOC level rises, the efficiency of charging the EV, as measured by its own SOC, decreases. For the factor concerning the state of charge of the ESS, a noticeable decline in the signal/noise ratio is observed as the factor's level ascends. Conversely, with regard to charging time, the trend reverses, indicating an increase in the signal-to-noise ratio as the charging time increases. This inverse dynamic highlight that higher SOC levels in the ESS correlate with a decrease in the signal-to-noise ratio. On the other hand, longer EV charging times are associated with an increased signal-to-noise ratio, suggesting improved outcomes under these conditions. A significant observation is noted at the 60% ESS

SOC level, beyond which the average response begins to decline markedly. This finding is crucial for optimizing the charging process, as it indicates a threshold beyond which higher ESS SOC values could lead to diminishing returns in EV charging efficiency. Tukey's confidence intervals, allow comparing the means of the factor levels pairwise. It is noted that there is no significant difference between the confidence intervals for the levels of ESS SOC. Checking the previously chosen 60% value, its CI does not differ from higher levels in terms of EV SOC. Also it provides a high EV SOC, so it may be the right level offering the optimum.

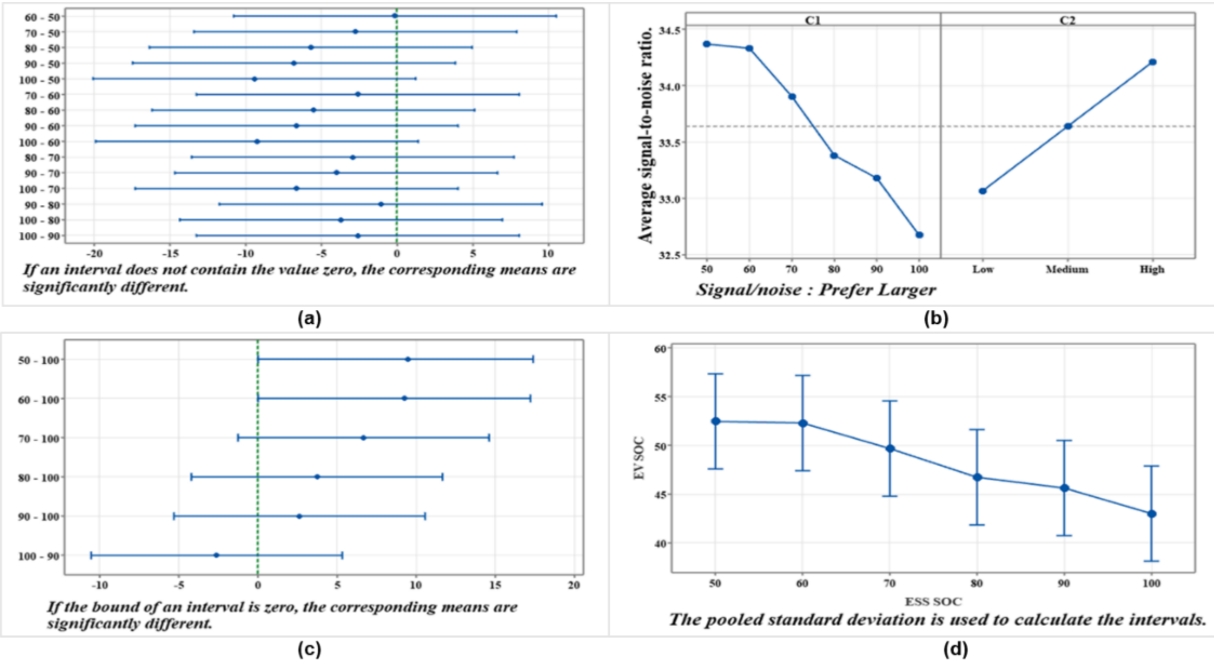

Figure 7. The results of ANOVA analysis: (a) Simultaneous Tukey 95% CIs. Differences in means for EV SOC; (b) Main effects graph for Signal-to-noise ratios. Data averages; (c) Simultaneous 95% Hsu CIs. Level average - the smallest of the other level averages for EV SOC; (d) Graph of EV SOC and ESS SOC intervals. 95% CI for the mean.

As with Tukey's analysis, Hsu's CIs show the differences between the mean levels for another factor. The Hsu method is used to compare each group mean with the best group mean. This shows comparisons between each factor level and the level with the highest mean. Several levels appear to be significantly different from the best mean, indicating differences in the effect of these levels on the response, except for levels 50 and 60, where the CIs are entirely above zero, which means that they are the best levels for our preference (we prefer the highest value). The lengths of the confidence intervals indicate the variability of the estimates of the means. A trend can be observed indicating that increasing levels of ESS SOC are associated with a decrease in EV SOC response.

According to Henry's line, most of points follow closely the expected linearity, with the exception of a few deviations at either end. This indicates that normality is respected, but with some extreme values. Furthermore, the plot of residuals as a function of fitted values, shows random dispersion. The absence of discernible patterns or trends in this graph indicates that the residuals are randomly distributed around zero. This randomness supports the homogeneity of variances assumption, meaning that the residuals have consistent variability across the range of fitted values.

Additionally, the histogram of residuals is intended to provide a visual sense of their distribution. A symmetrical bell shape would indicate a normal distribution of residuals. However, there is a slight asymmetry, suggesting a slight deviation from normality. Lastly, the graph of the residual values as a function of the order of observations shows some alternation of values. Yet, there is no clear trend or cyclical pattern, indicating that the independence assumption is reasonably met.

In summary, the homogeneity of variances and independence are reasonably well respected in this analysis. In addition, the results show that the right choice to make is 60%, given that this value for the ESS's SOC within buildings is the largest value offering a confidence interval above zero, as well as a high level of car charging at the charging point.

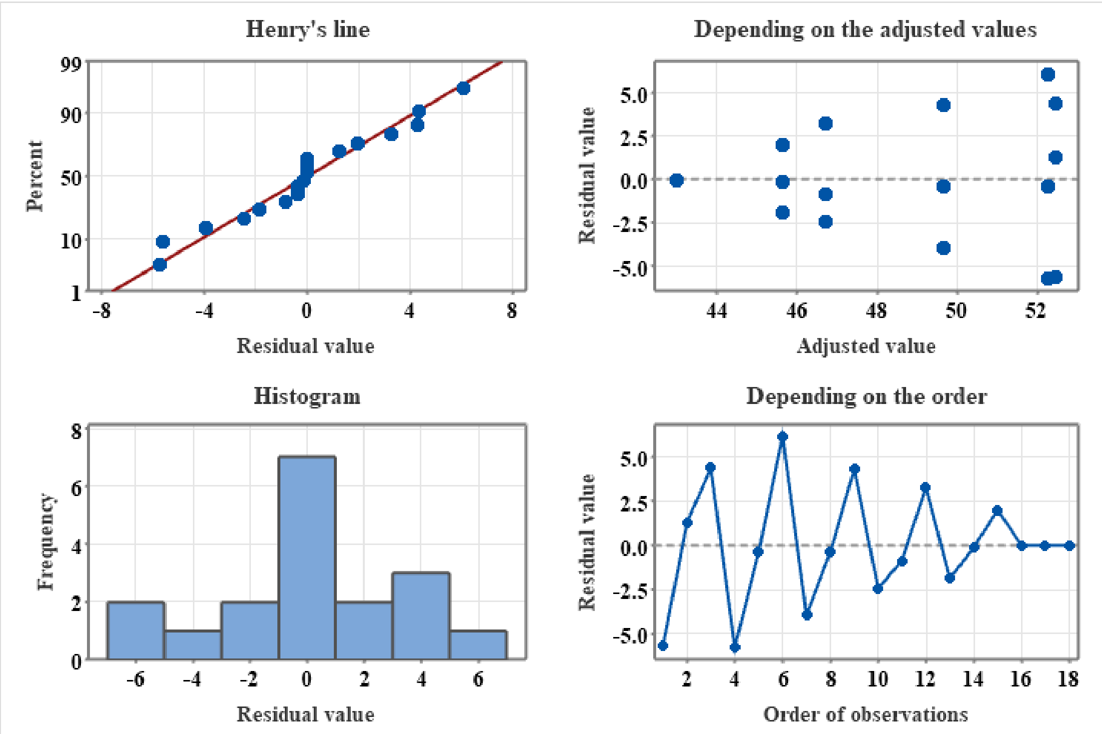

Figure 8. Diagrams of residual values for EV SOC.

4. CONCLUSION:

The suggested strategy was simulated and demonstrated favourable outcomes in charging the EV using surplus energy from five residential properties. It is recognized that maintaining an 80% SOC in the ESS is beneficial for meeting the peak energy demands of a dwelling and for ensuring energy availability during periods of low PV production, while also promoting the health and longevity of LiBs. In our vision for future smart cities and energy community projects, we posit that a 60% SOC in the ESS (which was found to be the best choice based on the Taguchi method analysis), complemented by PV production, could adequately meet the energy requirements of households, as well as supply the EV charging points. This approach allocates equitable importance to satisfying both the building's energy needs and the demands of the EV charging points, forging a synergy that not only maximizes efficiency and battery health but also aligns with sustainable urban development goals. By integrating such a strategy, smart cities can optimize their energy resources, prolong the life span of storage systems, and facilitate the widespread adoption of EVs, thereby contributing to a greener and more resilient urban energy landscape. However, the potential economic advantages of this recommended technique have not been taken into account within this study.

AUTHORS CONTRIBUTION: Amal Nefraoui: Formal analysis, Investigation, Software, Resources, Writing – original draft. Khalid Kandoussi: Investigation, Resources, Supervision, Visualization. Rabie Elotmani: Investigation, Visualization. Abderrahim Boutahar: Writing – review & editing.

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Conflicts of interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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