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Home Energy Management combining a welfare calculation and Vehicle-to-house technique for grid stability

Weiheng Lu

Guangdong Country Garden School, Guangdong, China

reedhang1115@qq.com

Abstract. The increasing adoption of electric vehicles (EVs) poses grid stability challenges. This study explores Home Energy Management (HEM) systems, facilitating bidirectional communication between users and energy providers to address these issues. We review HEM methods, including ZigBee, PLC control, and reinforcement learning, optimizing household energy usage. We investigate the incorporation of welfare calculation, accounting for occupants' well-being, and introduce the potential of Vehicle-to-Home (V2H) technology for enhancing energy resilience. Combining welfare calculation and V2H offers optimized HEM, prioritizing user comfort and decision-making efficiency. This report identifies research gaps and emphasizes the significance of delay-intolerant and delay-tolerant demand considerations. Battery charge-discharge conditions and utility welfare calculation are also discussed as critical facets of HEM. To solve the delay intolerant demand issue, EVs are used as storage devices to mitigate the peak load impacts using vehicle-to-house (V2H) technology. A scaled-down version ($1{:}10^6$) of the real UK electricity consumption system is used in the test. Simulation results verify that the proposed V2H system considering the welfare calculation can optimize the welfare level when one 60-kWh Tesla EV is involved in this scaled-down system.

Keywords: Home Energy Management, Vehicle-to-Home (V2H) Technology, Welfare Calculation.

1. Introduction

The increasing number of electric vehicles poses a threat to the current power system stability. Home energy management can potentially reduce the risk by incorporating bidirectional communications between the user and energy provider. Han et al. consider and analyse both the home consumption and renewable energy generation to minimize the energy bill based on ZigBee and PLC control techniques [1]. In [2]-[4], in order to optimize the convergence speed and house appliance energy consumption, the federated/deep/transfer reinforcement learning is proposed for managing multiple households. Erdinc et al. provide a mixed-integer linear programming-based framework for modelling a HEM structure [5].

Welfare calculation refers to an approach that takes into account not only the quantitative aspects of energy consumption but also the subjective well-being and comfort of occupants. This approach aligns with the broader shift toward more holistic measures of sustainability and quality of life. Several studies have explored the integration of welfare considerations into home energy management systems. For instance, researchers have developed frameworks to quantify the impact of energy-related decisions on occupants' comfort, health, and overall well-being [6]. This approach often involves the use of surveys,

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questionnaires, and qualitative assessments to capture occupants' preferences and perceptions. There is a need for unified frameworks that seamlessly integrate welfare considerations with V2H-enabled energy management strategies.

Vehicle-to-house (V2H) is a technology that enables bidirectional energy flow between electric vehicles (EVs) and residential buildings. This technique allows EVs to serve as energy storage units, capable of supplying electricity to the home during peak demand or grid outages. V2H integration has gained traction due to its potential to enhance energy resilience, reduce electricity bills, and support the integration of renewable energy sources.

For example, Xu et al. conduct the optimal power flow to maximize the energy exchange for the reliability enhancement by using V2H [7]. In [8], a vehicle-to-house (V2H) charge management based on the peak shaving method is proposed to minimize the peak loading at each individual house using a residential model-based control design. However, the above literature only considered how to reduce the risk level of the system while they did not take the welfare of users into account.

A growing body of research has explored the technical and economic feasibility of V2H systems, as well as their impact on grid stability and environmental sustainability. More sophisticated models are required to capture the dynamic and often complex behaviors of occupants in response to energy management interventions.

Indra's large-scale V2G trial, starting in 2022 with hundreds of participants until 2024 [9]. They use bidirectional electric vehicle (EV) charging technology that is designed to help the customer save money and the planet by leveraging surplus energy stored in the EV to feeder the users' home. Indra certified V2H enables seamless energy sharing between EVs and homes.

The integration of welfare calculation and V2H techniques presents a unique opportunity to optimize home energy management strategies that prioritize both energy efficiency and occupant well-being. However, the literature addressing this specific combination is relatively limited. Therefore, our contributions are summarized as follows:

- We proposed dynamic energy management strategies that consider occupants' comfort preferences and well-being using Human Readable Table alongside the availability of energy from EVs. This strategy aims to balance energy consumption patterns with occupants' needs, ensuring optimal levels of comfort while minimizing power stability risk.
- We investigated the V2H conditions that considers occupants' schedules, preferences, and well-being factors. These conditions can guide the V2H system to adapt energy transfer based on real-time energy demand and EV availability.

2. Methods

2.1. Performance Index

The risk level defined in this report is similar to Peak-to-average ratio (PAR), which is a concept commonly used in various fields, including the context of Vehicle-to-Home (V2H) technology. In the realm of V2H, peak-to-average ratio refers to the ratio between the highest energy consumption or demand (peak) and the average energy consumption over a given period. This concept plays a significant role in understanding energy utilization patterns and designing effective energy management strategies. Let's delve into a simplified introduction to peak-to-average ratios in the context of V2H:

$$Risk\ level\ (PAR) = \frac{Peak\ value}{Mean\ value} \tag{1}$$

In Vehicle-to-Home (V2H) systems, which involve utilizing an electric vehicle's (EV) battery to power a home, managing energy flow efficiently is essential. The peak-to-average ratio (PAR) is a measure used to assess the fluctuations in energy consumption or demand within a specific time frame.

In the context of V2H, the peak-to-average ratio considers the highest energy demand points—often referred to as the peak demand versus the overall average energy consumption. A high PAR indicates that the energy demand experiences significant spikes, potentially straining the power grid and resources during peak demand periods.

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For instance, during certain times of the day when multiple appliances are running, the energy demand may spike, resulting in a higher peak-to-average ratio. V2H systems aim to balance these peaks by utilizing the energy stored in the EV's battery during off-peak hours and distributing it when energy demand is at its highest.

By analyzing the peak-to-average ratio (PAR) in V2H applications, homeowners and energy management systems can:

- Optimize energy consumption patterns by using stored EV energy during peak demand.
- Reduce strain on the power grid during periods of high energy demand/improve the reliability through the home energy management
- Improve overall energy efficiency by aligning energy consumption with availability/reduce the energy bill for the customers

In summary, the risk level/peak-to-average ratio is a crucial metric in Vehicle-to-Home technology, enabling better management of energy demand and supply. Understanding and addressing the peak-to-average ratio contributes to a more sustainable and efficient use of energy resources within a V2H system, benefiting both homeowners and the broader energy ecosystem.

2.2. Human Readable Table

To enhance the precision of assessing customer welfare, we introduce the concept of the Human Readable Table (HRT) to gauge consumer satisfaction regarding energy consumption while considering the quality of services (QoS). This concept draws inspiration from the Infrastructure Interdependencies Simulator (i2SIM) [10]-[14], a system simulator developed at the University of British Columbia's Complex Systems Integration Laboratory, which models the interdependencies of diverse systems. We have several reasons for proposing the HRT for welfare calculation:

1. HRT enables utilities to take into account various aspects of quality of service (QoS) beyond just the quantity of energy consumed when evaluating user satisfaction.
2. Compared to mathematical formulations, the tabular format is more user-friendly and has a stronger theoretical foundation.
3. Restricting outputs to a finite number of states simplifies the process of surveying communities. For instance, it is more user-friendly to ask customers to provide responses in an abstract format (e.g., 50, 100, etc.) rather than specific numbers (e.g., 27, 83, etc.), as typically used in conventional utility calculations.
4. Discretizing the range of potential satisfaction levels derived from electricity usage not only reduces problem complexity but also mitigates the sensitivity of the solution to inaccuracies in data values.

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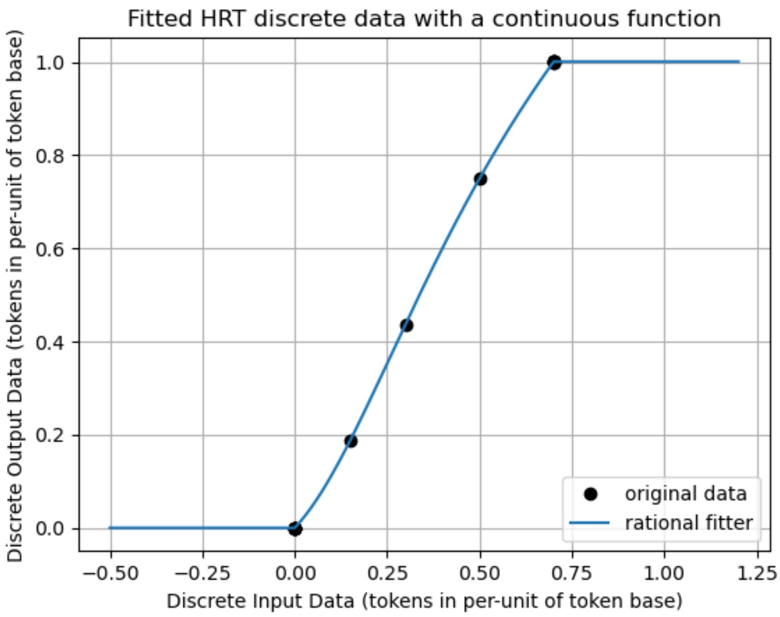

Figure 1. Example of the hyperbolic function in HRT [13].

The satisfaction level is an index that can be ranged, for example, from 0% to 100% and it is determined by a user's private characteristic preference, indicating the degree (percentage) to which one choice ranks above another. Because each HRT can have only one output, there is a unique relationship between individual input and the output (for example, In_1 and Y in Table 1), which is characterized by a hyperbolic function (Figure 1). Heterogenies categories are therefore converted to the same unit to avoid category-mistake. Note that even though five discrete states are defined in Table 1, in many situations where the knowledge of the information is very limited, three states (100, 50, 0) will still lead to useful results.

Table 1. An instance of welfare measurement using human readable table (HRT).

Output	Inputs			
Y: welfare (%)	In_1: The energy left in the battery, SOC (kWh)	In_2: Risk level (%)	In_2: Real-time price, $P_t(L_t)$ (€/kWh)	In_4: carbon emissions (kg/hour)
100	60	1	0.20	*< 0.4*
75	40	1.05	0.25	0.8
50	20	1.11	0.30	1.6
25	10	1.17	0.35	3.3
0	0	⩾ 1.23	0.40	*4.1 >*

In particular, the HRT is different from other input-output table used in systems modeling [15] because the inputs to the table can be any entity. Table 1 is an example of an HRT, where the output column is the welfare (satisfaction) level, Y, and the input columns are amount of energy left in the battery (In_1), real-time price (In_2), risk level (In_3), alongside how the energy is produced or if the consumed energy is environmentally friendly (In_4). If one QoS hits the bottom line of the user's predefined expectation (by surveying the specific community), then regardless if all the other inputs are in a high level, how "satisfied" that the consumed energy will be determined by the least available input.

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This allows us to easily see which service is limiting the output, which in turn, shows us where to allocate our effort to increase the total welfare level. In this report, $\mathrm{In}_1$and In_2 considered as the limiting input while other inputs in the table are assumed to be fully satisfied (no constraints). In mathematical terms, the output (utility) of a specific user is calculated as the function (Y) of N-nonlinear, independent eigenvectors, In_n, where n is the nth type of service and $n \in N$.

$$Y = min\left(f_1(\mathrm{In}_1), f_2(\mathrm{In}_n), \ldots, f_N(\mathrm{In}_N) \right) \tag{2}$$

In this example, as indicated in yellow (In_1input column), if only 10 kWh energy is provided left in the battery, then despite if it is a green energy (with extreme low carbon emission) or a very low risk level, the utility is limited to only 25%. To obtain a saturated point (the 5th dot in Figure 1) for a full output, the user requires 50 kWh more energy stored and risk-free power delivery. Therefore, this table assists the user to find a saturation point. After this point, no matter how much power is stored, there is no more welfare incremental to users.

2.3. Delay Intolerant/Tolerant Demand

In the context of home energy management, "delay-intolerant" and "delay-tolerant" demand refer to how sensitive certain energy-related activities or requirements are to delays. Let's break down what these terms mean in the context of home energy management:

Delay-Intolerant Demand in Home Energy Management: Delay-intolerant demand in home energy management pertains to activities or services related to energy consumption that require immediate attention and timely fulfilment. This could include scenarios where energy needs must be met promptly to avoid disruptions or inconveniences. For example, if there's a sudden high demand for electricity due to running multiple appliances at once, delay-intolerant demand would ensure that power is delivered without delay to prevent overloads or outages.

Delay-Tolerant Demand in Home Energy Management: Delay-tolerant demand in home energy management refers to activities that have some flexibility in their timing and can withstand minor delays without significant negative effects. These are situations where energy consumption can be adjusted within a certain timeframe without causing inconvenience or disruption. For instance, scheduling the operation of certain appliances, like a dishwasher or a washing machine, during off-peak hours when energy demand is lower demonstrates delay-tolerant demand.

Is EVs charging delay-tolerant or -intolerant demand? EV charging might not be that urgent at some conditions, for example, the vehicle is not going to be used in the following day or where there is a high energy demand already; EVs charging can also be urgent when the energy left in the batteries is low (the EV is planned for the next commute immediately) or the utility fare hits the lowest point during the day (the house owner pays less energy bill by doing so). Therefore, EVs charging can be both delay-tolerant and -intolerant demand depending on the situations and state of charge of the batteries. The report provides specific conditions in Section 2.4.

Understanding the type of demand—whether it's delay-intolerant or delay-tolerant—within the context of home energy management is crucial for optimizing energy usage and maintaining a stable energy supply.

Introduction of V2H, V2G, and V2V techniques:

- Vehicle-to-Home (V2H) enables EVs to supply stored energy back to households using bi-directional EV charging solutions. V2H optimizes energy use, reducing costs and emissions, enhancing grid stability. V2H ensures seamless energy sharing between EVs and homes;
- Vehicle-to-Grid (V2G) enables electric vehicles to both draw and supply power from/to the grid. This innovation enhances grid stability, integrates renewables, and offers economic benefits by using EV batteries as flexible energy storage, creating a symbiotic link between transportation and the electricity system;

Vehicle-to-Vehicle (V2V) technology facilitates direct communication between vehicles, enhancing road safety and traffic efficiency. Through real-time data exchange, V2V enables vehicles to share

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information about speed, location, and potential hazards, reducing accidents and promoting a safer, more connected driving environment.

2.4. Battery Charge-discharge Conditions

There are several situations (S1-S6 are listed in this section) that may occur in the control decisions. They are implemented by the model-based ECSs accordingly based on different operation signals. Figure 2 shows the real national power demand of the UK [16] on Aug. 1st 2022 and it illustrates the upper (DL_t^{max}) and lower (DL_t^{min}) boundaries. The grid risk increases when the power demand exceeds the boundaries. The V2H is initialled based on different conditions.

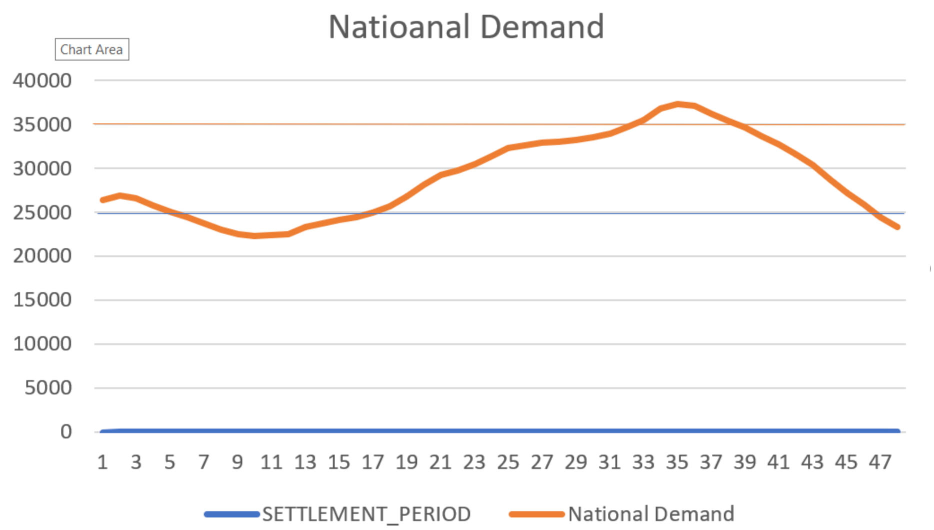

Figure 2. The real national power demand of the UK [16] on Aug. 1st 2022.

Table 2. Battery charge-discharge conditions.

Conditions	Descriptions	Charg-eable	Dischar-geable	V2H?
1	The EV is broken	☹	☹	☹
2	$T_{departure}(7am) < t(2pm\ for\ example) < T_{arrival}(5pm)$: this condition indicates that the EV does not park at home, and this is why the V2H technique cannot be implemented.	☹	☹	☹
3	$t < T_{departure}(7am)$ or $T_{arrival}(5pm) < t$ and $SOC_t(20\%) < SOC_t^{min}$ (30%): in this condition, the EV is parked home, and the state of energy (SOC_t) is below the pre-determined set point of the minimum state of energy. Therefore, the EV is chargeable but not dischargeable in this case.	☺	☹	☺ and ☹
4	$t < T_{departure}(7am)$ or $T_{arrival}(5pm) < t$, and $DL_t^{min}(25000MW) < DL_t < DL_t^{max}$ $(35000MW)$: although the EV is parked at home, there is no need to charge or discharge as the load demand is within the limitation boundary.	☺	☺	☹

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Table 2. (continued).

5	$t < T_{departure}(7am)$ or $T_{arrival}(5pm) < t$, and $DL_t^{max}(35000MW) < DL_t$: the EV is parked at home, and the load demand exceeds the upper boundary/limitation	☹	☺	☺
6	$t < T_{departure}(7am)$ or $T_{arrival}(5pm) < t$, and $DL_t^{min}(25000MW) > DL_t$:	☺	☹	☺
7	…	…	…	…

*The "smile" face indicates that the action can be done, vice versa.

The variables in the above table will inevitably affect the performance of the V2H technique. They are:

- SOC_t^{max} : maximum state of energy that can be stored in the EV's battery (the battery's capacity)
- SOC_t^{min}: minimum state of energy stored in the EV's battery for the emergency use/next travel (based on the owner's preference)
- SOC_t^{thr}: threshold of minimum energy charging amount
- $T_{arrival}$: the time when the EV arrives at home
- $T_{departure}$: the time when the EV departs
- DL_t^{min}: minimum demand limitation/threshold
- DL_t: House demand at time t
- DL_t^{max}: maximum demand limitation/threshold

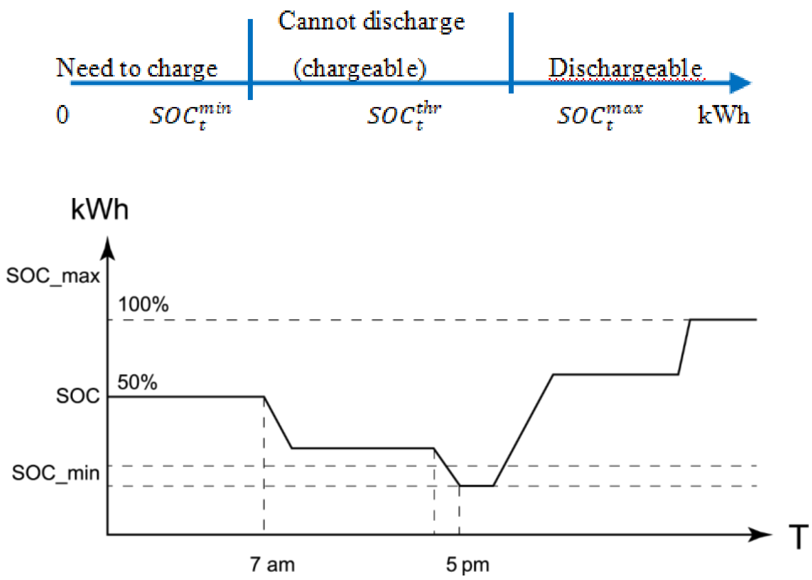
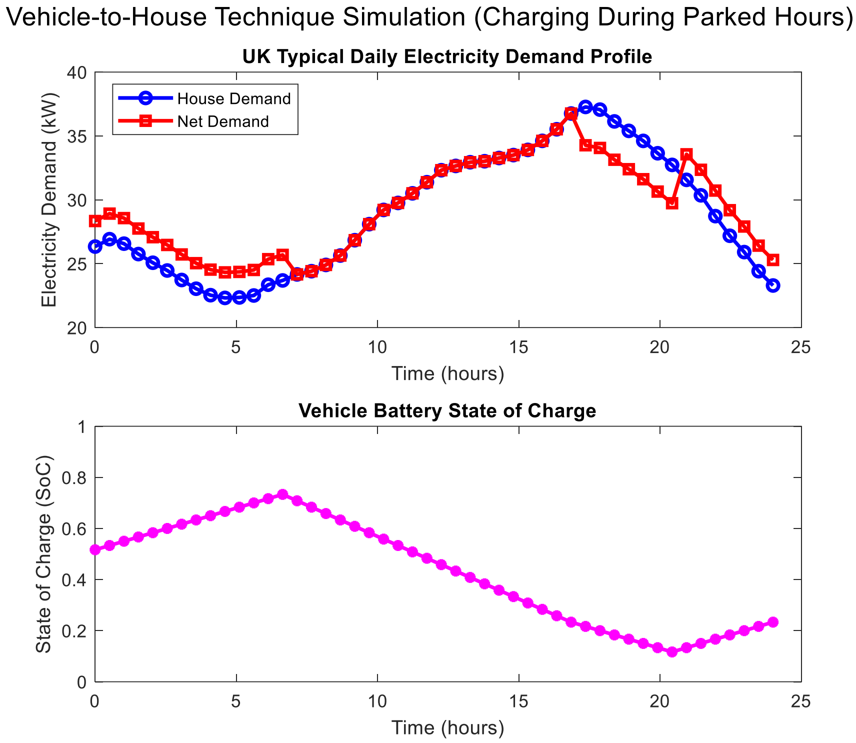
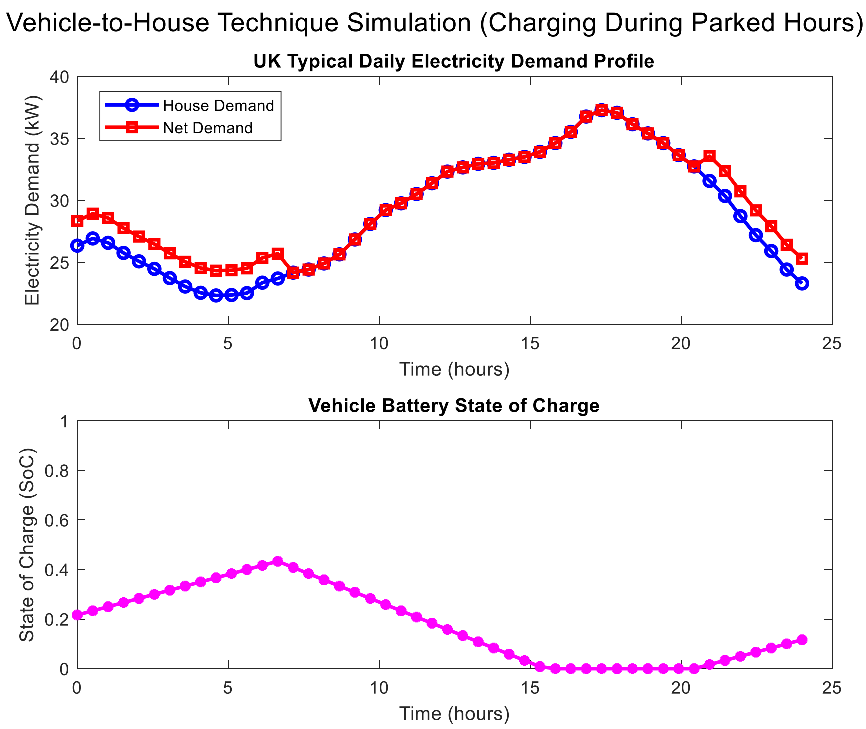


Figure 3. An illustrative example of SOC variation during the day.

3. Tests Analysis



(a)



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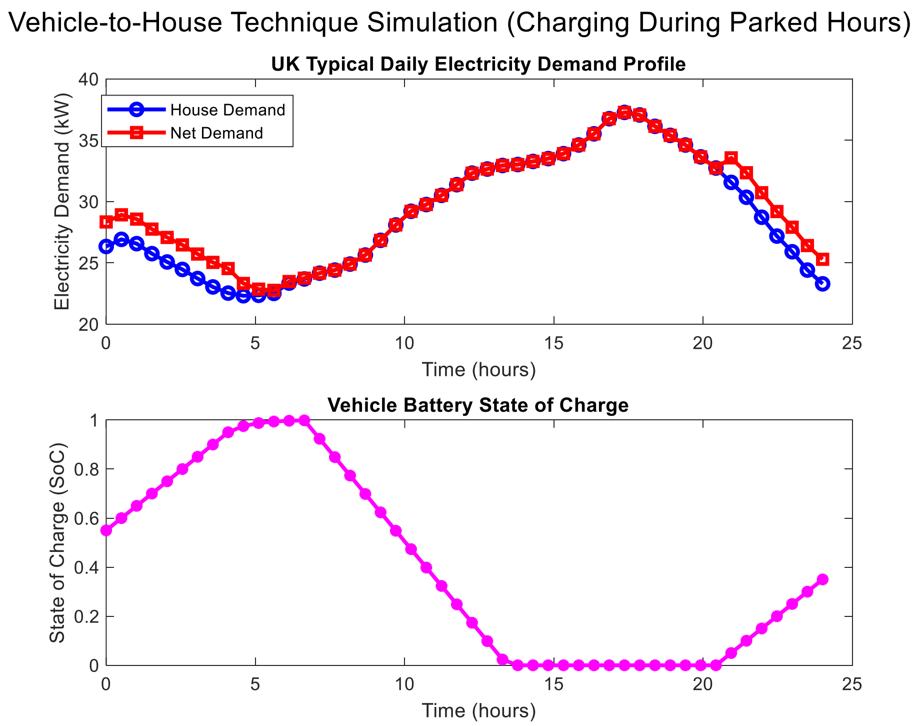

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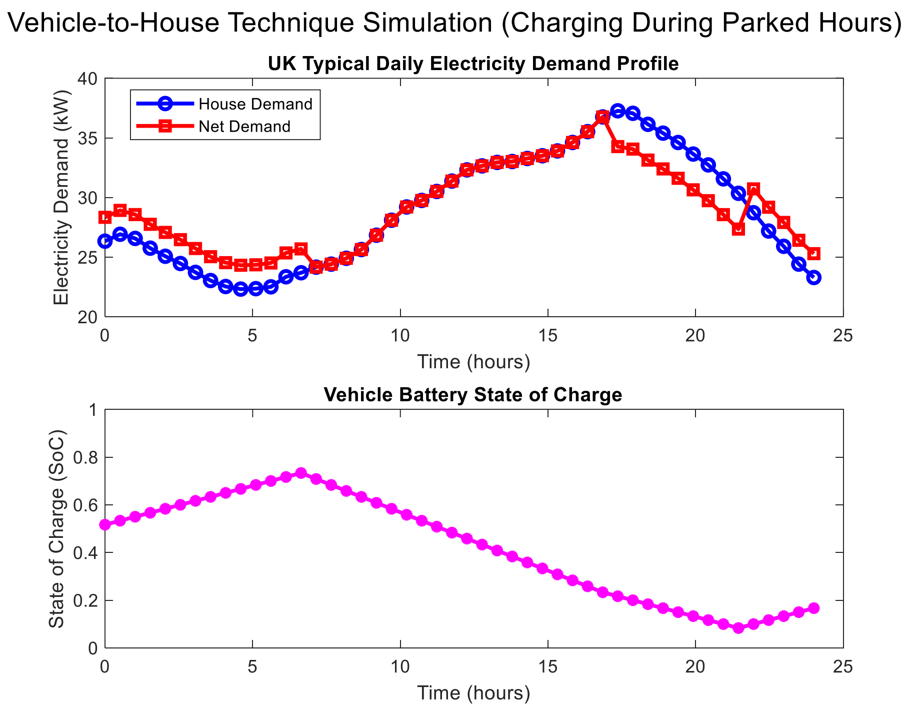

(d)

Figure 4. (a) V2H technique applied with initial parameters (the benchmark); **(b)** $SOC_{\ t=0}$ is reduced from 50% to 20% with other parameters unchanged; **(c)** $SOC_{\ c}$ is reduced from 60kWh to 20kWh with other parameters unchanged; **(d)** DL_t^{max} is reduced from 32kW to 30kW with other parameters unchanged.

Figure 4 (a) is the benchmark and its relative parameters is listed in Table 2. the upper figure in Figure 4 (a) illustrates the house demand with and without V2H applied. The blue curve indicates a scale-down UK daily power demand variation for a small community) without V2H applied. We notice that the peak demand occurs at around 18:00 pm with totally 36 kW power generation is required. Following the predefined conditions and constraints, V2H is implemented at this time. The power demand is reduced from 36 kW to 33kW (the discharge rate is set to 3kW). When the house demand is below 31 kW (around 20:00 pm), the V2H discharging is no longer needed to feed the house demand. The EV starts charging (the red curve jumps back higher than the house demand) and the SOC increases gradually. In Scenario 2, we change the initial SOC from 50% to 20% (Figure 4 (b)), we notice that the SOC (purple curve) hits 0 at around 16pm before arriving home. This means there is no energy left in the car and power discharge cannot be implemented. In another words, V2H is not initialed (the blue line and the red line are overlapping in Figure 4 (b) during the peak hours. In Scenario 3, the battery capacity is changed from 60 kWh (Tesla model-S [17]) to 20 kWh. Compared with the purple curve with the benchmark, the change rate of SOC in this scenario is greater (the lower figure in Figure 4 (c)). It reaches 100% easily before departure and reduces to zero before arriving home. That is the SOC is more sensitive when we change the capacity with the charge and discharge rate remain the same. The only change in Scenario 4 is the peak demand limitation, we switch the number from 32 kWh to 30 kWh, which means we reduces the upper boundary. As is shown in Figure 4 (d), the EV re-charging is delayed (around 22:00) compared with that in Figure 4 (a) (around 20:00). Please note that the reference DL_t^{max} is based on the house demand (blue curve) not the net demand (red curve).

Detailed settings of parameters of these four scenarios are displayed in the following Table 3.

Table 3. Single Parameter tuning for V2H Analysis.

	Parameters
Figure 4 (a)	$SOC_{\ t=0} = 50\%$ $SOC_{\ c} = 60\ kWh$ $DL_t^{max} = 32kw$
Figure 4 (b)	$SOC_{\ t=0} = 20\%$ $SOC_{\ c} = 60\ kWh$ $DL_t^{max} = 32kw$
Figure 4 (c)	$SOC_{\ t=0} = 50\%$ $SOC_{\ c} = 20\ kWh$ $DL_t^{max} = 32kw$
Figure 4 (d)	$SOC_{\ t=0} = 50\%$ $SOC_{\ c} = 60\ kWh$ $DL_t^{max} = 30kw$

4. Conclusion

In conclusion, this comprehensive study delves into the critical aspects of Home Energy Management (HEM) systems in the context of the increasing adoption of electric vehicles (EVs) and their impact on grid stability. The research explores various HEM methods, including the incorporation of welfare calculation is introduced as a means of considering occupants' well-being in energy management decisions, aligning with the broader sustainability shift.

One of the standout innovations discussed in this report is the Vehicle-to-Home (V2H) technology, which enables bidirectional energy flow between EVs and residential buildings. This technology has the potential to enhance energy resilience, reduce electricity bills, and support renewable energy integration. However, it's important to note that the welfare of users must be taken into account when implementing V2H systems, ensuring a holistic approach to energy management. The concept of the Human Readable Table (HRT) is introduced as a tool to assess customer welfare regarding energy consumption and quality of service, offering a more user-friendly and comprehensive approach. Furthermore, the report addresses the critical distinction between delay-intolerant and delay-tolerant demand in HEM and how EV charging can fall into both categories depending on various factors.

Overall, this research underscores the importance of considering both technical and human-centric aspects in designing effective HEM systems, particularly when integrating V2H technology. By optimizing energy usage while prioritizing user comfort and well-being, we can pave the way for a more sustainable and resilient energy future.

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