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Establishing a Case for Predictive Machine Learning to Optimise Vehicle-to-Grid Charging for Reduced Carbon Intensity in the Built Environment

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Summary

This paper presents analysis to establish a best case for the application of short-term future prediction of vehicle usage patterns and local energy demand to improve operation of bidirectional Vehicle-to-Grid (V2G) or Vehicle-to-Building (V2B) charging for a university fleet of vehicles. A control scheme based on simulated perfect 48h ahead prediction is compared through battery cycling simulation to unmanaged charging and a real-time rule-based control scheme. Results show that in the ideal case, predictive V2G operation can significantly reduce carbon intensity of the studied fleet versus unmanaged charging and controls based on real-time data. This establishes that the potential for applied predictive control managing multi-system data for V2G is likely worth the additional complexity and computational requirements. The challenge in implementation lies in handling uncertain predictions from an applied machine learning model.

Keywords: V2G (vehicle to grid), V2B (vehicle to building), user behaviour, sustainability, simulation.

1 Introduction

The Intergovernmental Panel on Climate Change (IPCC) reaffirmed with high confidence the near-linear relationship between anthropogenic CO2 emissions and the global warming, and the requirement to reaching net-zero CO2 emissions to stabilise global temperature [1]. In the city environment, this requires change across many sectors and the integration of systems such as transport, buildings and the energy grid. In the UK, the transport sector is the largest emitter of greenhouse gases responsible for 27% of the total emissions [2]. According to the IPCC report about mitigation of climate change [3], “electric vehicles powered by low emission electricity offer the largest decarbonisation potential for land-based transport, on a life cycle basis” with high confidence (p. 41).

As the transport sector transitions towards electric vehicles (EVs), management of EV charging demand is essential to ensure minimal impact on electrical grids and to minimise carbon emissions; however there is also potential to use EV batteries to support electrical grids as an energy store though bidirectional Vehicle-to-Grid (V2G) charging. Through the increasing availability of data from vehicles, vehicle users, renewable energy generation, localised energy demand, and electrical grids, there is insight to be gained in the interaction between different systems in order to optimise EV charging. Challenges lie in both the co-ordination of data from multiple sources, and in effective use of data across systems.

This paper presents a brief overview of how predictive machine learning and intelligent control can be applied to address energy optimisation problems across related energy systems. An examination of the potential benefits of the availability of real-time data, and future predictive data is presented for a local vehicle-to-grid (V2G) control system managing fleet electric vehicle charging, building energy demand, local renewable energy generation and grid carbon intensity. The control problem was designed to address the challenges of introducing EVs into an existing vehicle fleet – where local electrical demand is increased, this will have impacts on electrical infrastructure, peak electrical demand and total carbon emissions from grid import to the local system. The case for managing EV charging in some form to address these issues is well established [4], however in many cases the difference made by additional levels of complexity in charging management is not clear. A primary aim of this study was to establish separately to the success of any particular predictive approach, a theoretical upper limit to address whether the increased complexity and cost of an applied intelligent vehicle-to-grid control system is justified by marginal benefits against simpler control schemes.

2 Energy applications of Machine Learning and Optimisation

The increasing availability of 'Big Data' has potential for applications across a number of interconnected systems, including: energy, mobility, healthcare, planning and policy making [5]. There is potential for data analytics and machine intelligence to both identify opportunities for improved inter-system operations, and to optimise operations in real time. Existing research has covered a number of energy-focused applications of machine learning/optimisation processes, including: predictive energy management in buildings [6], renewable energy storage [7], and electric vehicle charging/vehicle-to-grid operation [8].

Emerging from these fields are a number of common goals: the need to understand energy requirements of users, the ability to meet demand while enacting energy saving measures where possible, and the ability to balance demand against changing external factors. In many cases, this requires an understanding of the difference between energy demands that are time sensitive and those that can be offset to better utilise resources. For this purpose, prediction of near-future demand can be used (e.g., day-ahead energy trades, need to preheat/cool building spaces, ensuring EV battery charge sufficient to make required journeys). Successful optimisation of processes at a community, city or greater level requires co-ordination of multiple data systems, presenting further technical and ethical challenges. As the complexity of methods applied for system optimisation increases, the additional operational benefit should be great enough to justify the additional computational or data requirements. For example, in the space of predictive energy management in an office setting, study has suggested that perfect foreknowledge of future building occupancy did not significantly improve on controls for air conditioning operation beyond a real-time reactive control scheme in the conditions tested [9].

Specific to the problem of EV charging management, multiple factors may impact on the charging timing, such as local building energy demand, carbon emission, vehicle demand and the distance of the vehicle to the chargers. This calls for smart charging schemes with the integration of intelligent methods. Additionally, V2G technology has potential to be applied in a number of contexts, including grid Firm Frequency Response (FFR), grid load balancing, or behind-the-meter balancing of local demand. Each of these services has different requirements on the information needed to make charging decisions and the time horizon before which energy must be committed. In vehicle-to-grid operation, machine learning techniques have received attention in the smart control of various tasks, including in predicting vehicle availability [10], vehicle battery capacity [8], [11]–[13], parking location [14] and parking space [15]. The way that machine learning is applied is by formulating the control tasks as prediction tasks, thus, facilitating the interaction between experts and machine learning systems. Various machine learning methods, ranging from conventional machine learning models [10], [11], [15] to deep learning methods [8], [12], [13], have been investigated in forecasting the behaviour of the system by learning knowledge from historical data. The use of machine learning supports the decision-making process in the vehicle-to-grid operation to make more reliable and more efficient decisions.

3 Methodology

Analysis was conducted using a simulated control system for bidirectional electric vehicle charging as an energy store in a local system consisting of real historical data from vehicles, building electrical demand, and renewable energy generation within a university campus environment in the United Kingdom. In the simulations, energy demand in excess of the energy provided by the local renewable system was assumed to be imported from the electrical grid. In contrast to existing works predicting vehicle capacity for energy trading with the wider grid, the application developed in this paper was broadly aimed at maximising behind-the-meter benefits of V2G/V2B in a localised energy system in order to balance existing building demand and minimise stresses on local infrastructure, building upon previous work based on maximising the benefit of rule-based controls [16]. Operation of the fleet vehicle charging was aimed at reducing overall carbon intensity of energy imported by the local system as a whole through the combined goals of increasing local self-consumption of renewable generation on site, offsetting vehicle charging demand to off-peak times for grid carbon intensity, and using the vehicle battery to offset carbon by discharging energy to the local building or grid during high carbon intensity periods.

The primary finding desired here was to establish how much of a difference can be made by the application of optimisation techniques beyond simpler static or dynamic rule-based control schemes, given the significant additional complexity involved in building and applying appropriate predictive and optimisation processes to controls in this system. To that end, this work focussed on building an 'ideal' upper limit specifically for carbon savings in a space where, realistically, a control system would need to simultaneously consider carbon savings, energy costs, battery life preservation, and local electrical limitations.

The vehicles used for this study comprised 22 vehicles from a subsection of the university fleet, of which the majority are currently internal combustion vehicles. Journeys and mileage of this fleet were tracked for a one-year period Jan-Dec 2019, from which charging demand was estimated based on mileage and average energy consumption of an equivalent electric vehicle model. Building energy demand data was taken from the buildings immediately around the main parking location of these vehicles. After first analysis, 3 vehicles were omitted from further study as it was found they did not spend enough time at the main parking site to recharge their estimated demand, leaving 19 vehicles for the remainder of this study.

The simulation process was conducted by iterating through the year of historic data as if the data was arriving in real time. The simulated control would then use the data currently available to decide on the charging action taken for each vehicle at each timeslot in the year. The following analysis presents simulation results of total system energy import, carbon intensity and vehicle battery charging in the simulated vehicle-to-grid system in the following control scenarios:

a) Baseline of building demand minus renewable generation, without vehicles.

b) Baseline plus vehicles with unmanaged EV charging, where vehicles charge at full power as soon as they arrive at the charger location.

c) Baseline plus vehicles with 'ideal' predictive smart charge, assuming perfect predicted 48-hour future demand from buildings, vehicle users etc. – where perfect predicted values were simulated by using future data directly.

d) Baseline plus vehicles with static rule based V2G control scheme based on pre-defined thresholds and real-time data without future prediction as summarised in Table 1. Full details of this method can be found in the work of Waldron et al [16].

e) Baseline plus vehicles with 'ideal' bidirectional V2G control, assuming perfect predicted 48-hour future building demand, vehicle use etc. – where perfect predicted values were simulated by using future data directly.

Table 1: Static V2G Charge Scheme

State Description				Charge Instruction			
State	Local Renewables	Grid CO2	Local Demand	High SoC (>90%)	Med SoC (50%<90%)	Low SoC (20%<50%)	Very Low SoC (<20%)
1	H	-	-	Delay	Charge	Charge	Charge
2	L/M	L	-	Delay	Charge	Charge	Charge
3	L/M	H	-	Discharge	Discharge	Delay	Charge
4	L/M	M	H	Discharge	Discharge	Delay	Charge
5	L/M	M	M	Discharge	Discharge	Charge	Charge
6	L/M	M	L	Delay	Charge	Charge	Charge

(L: low, M: medium, H: high)

The 'ideal case' charging was calculated as described in Algorithm 1. This calculation process was designed to ensure that vehicles will always be recharged in the medium term, but the system can offset charging to a future day if this will not impact operation. The system will prioritise self-consumption of local renewable energy generation where the renewable generates a surplus relative to the local building demand, then optimise for minimal CO2 production from local system energy imports from the grid. It should be noted that this calculation does not account for management of vehicle charging to reduce existing peak demand times of the building – exact calculation of an optimal strategy would require a value to be placed on which goal is more important when CO2 minimisation and peak minimisation conflict. To avoid skewing results by setting an arbitrary priority between these goals, the 'ideal' system in this case was aimed only at CO2 reduction.

Algorithm 1 - Simplified algorithm for calculation of optimum charge strategy given perfect 48 demand prediction

Per 48h future window:

1. *Calculate cost for each timeslot:*

If renewable generation > building demand:

cost = building demand - renewables

else:

cost = grid CO2 intensity

2. *Per vehicle in the fleet:*
    a. *Assign timeslots to charge, starting from lowest cost available slots, until battery has been recharged to full by end of 48h*
    b. *(V2G control only) Assign from the remaining available timeslots equal charge/discharge events in the lowest/highest cost slots respectively until no timeslots remain or the difference in CO2 is less than 10gCO2/kWh*
3. *Assign first 24h of proposed instructions to each vehicle. Move 24h ahead, recalculate.*

4 Results

A summary of the simulated system operation under the different vehicle charging scenarios is shown in Table 2. Where the system both imported and exported energy to the grid, net total energy was taken as the sum of imports minus exports. CO2 was calculated for each timeslot of the year based on total import or export from the building-renewable-vehicle system. Where the system exported energy to the grid, this was counted as a CO2 saving at the grid carbon intensity during the time of the export event.

It can be seen that the addition of EV charging to the building-renewable-grid system increases overall energy import in all scenarios. Total energy import to the system was largely the same through all scenarios including vehicle demand, with minor differences between scenarios explained by differing vehicle state of charge at the end of the simulation. With managed charging incorporating data from the grid, building, and renewable systems, the average carbon intensity of the system was reduced. Comparing the two charging-only scenarios, it was observed that in the 'ideal smart charge' case, management of charging can effectively reduce the carbon intensity of the system relative to unmanaged charging by deferring EV charge to the lowest intensity times of day.

Both of the simulated V2G scenarios, where bi-directional charging was used to strategically store and release energy using the vehicle battery, showed a greater decrease in total system carbon intensity. However, the 'ideal' case assuming perfect foreknowledge of future vehicle demand, grid intensity etc. showed a significantly larger benefit to operating V2G, with the fleet of 19 vehicles being used to effectively decrease both the carbon intensity and the total amount of CO2 caused by imports to the system.

Table 2: EV charge simulation results summary

	Baseline System Demand	+Unmanaged EV Charging	+Ideal Smart Charge	+Static V2G Control	+Ideal predictive V2G
Net Total Energy from Grid (kWh)	912483	926512	926500	926238	926512
CO2 from 1 yr system net Import (kgCO2)	199711	203029	201678	200969	193466
Avg. System CO2 Intensity (gCO2/kWh)	194.1	194.6	193.3	192.7	185.5
Effective CO2 Intensity of Fleet Demand (gCO2/kWh)	n/a	236.5	140.4	83.0	-445.1

In further examination of the V2G charging scenarios, the average 24-hour energy transactions between the vehicle fleet and the rest of the system are visualised in Figure 1 in comparison to the unmanaged charging scenario. It can be seen that during unmanaged charging, vehicles typically actively charged during the hours of 15:00-18:00, corresponding to higher CO2 intensity periods of the day. However, the vehicles were not engaging with the charging system for most of their plugged-in time, as seen by the smaller overall daily peak in energy transferred. By contrast, both V2G scenarios actively engaged the battery of all vehicles in the fleet for a majority of their plugged-in time, either by charging or discharging. This causes higher energy transfer peaks than occasional unmanaged charging. One additional behaviour to note is the difference in action around 18:00-21:00 between the two V2G scenarios, which is likely specific to the particular use case studied. The static rule-based V2G was seen to discharge heavily from batteries in the morning before the vehicles leave for weekday activity. As such, when vehicles return at the end of the working day, the battery level is more likely to be low or very low, leading to less discharge, or in some cases charge, during the peak period. The 'ideal V2G' scenario, with predictive foreknowledge of future activity and CO2 levels, prioritised discharge during the CO2 peak 18:00-21:00 over heavy discharging in the morning.

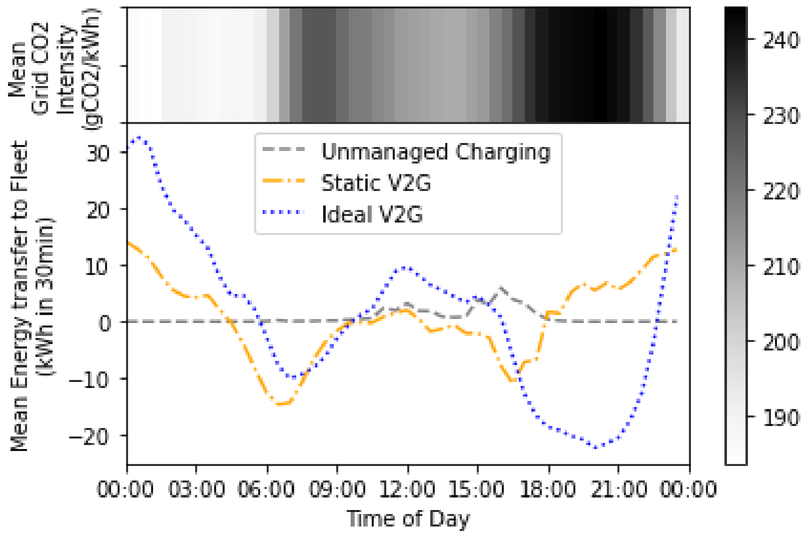

Figure 1: Average 24h energy transfer to whole fleet over 1 year simulation under the three proposed charging schemes

The impact of energy transfer from the fleet on the average daily profile of CO2 production for the local building-renewable-vehicles system is shown in

Figure 2. With unmanaged EV charging, the daily peak of carbon-intensive energy import was increased relative to the baseline system. However, with the two V2G schemes, the load of EVs was largely deferred to lower-intensity times of day. Additionally, vehicles discharging to the building/grid when CO2 was high effectively allowed reductions in emissions from the building demand during times of peak grid carbon intensity.

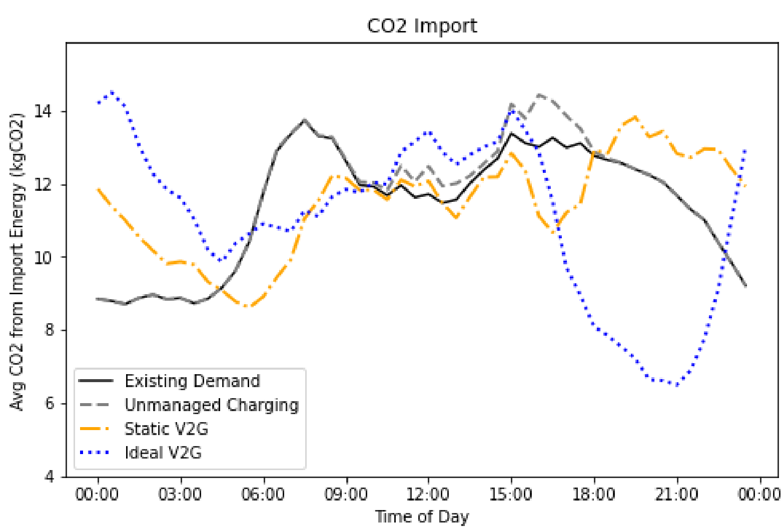

Figure 2: Average 24h CO2 Import over 1 year simulation under the three proposed charging schemes

These findings reaffirm that V2G vehicle charging can provide benefit through supporting energy systems as a distributed energy store. Further, the way that this energy store is managed can have a significant effect on the benefit provided by this system. The availability of additional data (from measurement of demand in real time, up to machine learning predicted future demand) can give the opportunity for significant reductions in operational carbon emission from the system as a whole, but at the cost of higher data sharing needs, computational and infrastructure requirements. The significant marginal benefit of the 'ideal' optimum charging scheme informed by predicted future data suggests that predictive V2G is a goal worth pursuing over real-time reactive controls. While real-time energy data and rule-based controls already provide significant reductions in the impact of additional EVs on local systems, the benefits were clearly increased by the availability of future demand data for V2G operation optimised over a 48-hour future horizon, such that the net effect of the introduction of vehicle charging in this simulation was carbon saving despite the additional energy load on the system.

5 Discussion

A number of challenges exist in the move towards applied intelligence in vehicle charging management. One important consideration is how the problem is framed to implement predicted data to inform control decisions. A potential approach is to build control decisions into the predictive process, such that predictive outcome is a control decision without explicitly predicting future demand. This allows the use of widely investigated conventional classifiers [17] and deep learning models to support the decision making process.

As an alternative to deriving control actions directly from system status, it may be beneficial to separately build models to explicitly predict future demands, which could then be passed as an input to controls for any related energy systems (e.g. vehicle charging, building heating management, energy storage). In this case, the predicted data could be applied in several ways:

- Dynamic setting of thresholds for a rule-based approach similar to the real-time control scheme presented in this paper.
- Full computation of mathematical optimum under a pre-defined set of conditions as in the 'ideal' simulation presented in Algorithm 1 – for more complex applications than studied here, this computationally intensive approach is likely impractical as the number of conditions grows and thus is not considered viable beyond small-scale proof of concept studies.
- Intelligent methods to seek optimum strategy without full computation, for example surrogate-assisted optimisation [18].

The ideal approach depends on the requirements of the system and what goal, or goals are being optimised – this study considers a relatively simple problem to keep the explicit calculation of optimum strategy computationally viable and without arbitrary ranking of conflicting goals. This approach represents a best case in terms of carbon reduction and local demand management, but could be extended to more complex problems balancing battery longevity, financial cost minimisation and other factors. In real-life application, the uncertainty of predicted future demand must also be accounted for in control decisions. Given that there is always some level of unpredictability inherent in demands dependent on human behaviour, perfect knowledge of future events is an upper limit that can be approached, but never attained. This means that any real-life application of a predictive V2G in this system would likely fall somewhere between the real-time reactive and ideal predictive scenarios.

Although intelligent methods could potentially produce more promising charging schemes, a number of key challenges have to be addressed in the aspects of technical issues, data management, data ownership, infrastructure and ethical requirements.

5.1 Technical challenges

The accuracy and generalisability of machine learning highly depend on the quantity and quality of input data [19]. This leads to requirements on the data collection and processing procedures to acquire useful information from a large and multi-sourced data set. In some application scenarios, the quality and the amount of data is limited, which leads to a limitation on the performance of machine learning models [7].

Another key issue is to use relevant features for representing the data set. With only a small subset of features, there is a corresponding decrease in the generalization of the machine learning models [20]. Identifying potentially relevant features from the raw data rely on some degree of the manual judgement of experts. There are some related works investigating useful features in different tasks of vehicle-to-grid operations [8], [10], [14], [21].

In building machine learning models, the main challenge is to identify the appropriate methods. The hyperparameter tuning and determining suitable learning schemes requires efficient experimental design and comprehensive evaluation. Since the widely studied learning methods are based on different learning schemes, the comparison between them could potentially help gain a better understanding of the data set. Recently, the development of automated machine learning brings more convenience in determining suitable learning models. AutoML has been investigated in [14] to relieve experts from the iterative and time-consuming process for determining learning methods in predicting vehicle location.

The integration of the model output and the system decision process requires further attention. Firstly, the model performance in the prediction error should be carefully considered in the decision process for producing accurate and reliable output that can appropriately account for some error in prediction without sacrificing the overall goals of the control task. Some studies [13] consider the use of online machine learning to update prediction models over time, reduce prediction error as the system or behaviours change. Secondly, for applications with prediction time horizon requirements, there could be a trade-off between the algorithm effectiveness and its complexity.

5.2 Data management and infrastructure

Managing data from different sources in real-time poses challenges in storage, maintenance, and communication [5] because the data flows are varied in different structures and types. Co-ordination of such data requires appropriate data handling infrastructure across multiple systems.

Data security is one of the key issues in the application of smart control in vehicle-to-grid operations, which could bring risks for the whole process. This creates the demand for the investigation of new and advanced methods to guarantee data security in smart control schemes [5].

5.3 Ethical requirements

Prediction of future demand data in a V2G system typically requires a large volume of data from vehicle users. There are a number of ethical challenges in ensuring that this data is collected, processed, stored and interpreted in an appropriate way. Location data from vehicles and users is classed as personal data – this is potentially sensitive and can be easy to identify the individual from a limited number of locations [22]. Data and predictive outcomes sharing between multiple control systems could provide a potential avenue for leaks of sensitive data without appropriate management.

6 Conclusion

This paper presents an examination of the upper limits of the potential for real-time data, predictive machine learning and intelligent optimisation to improve the operation of vehicle-to-grid (V2G) control and allow for further reduction of carbon intensity to be achieved by integrating data from multiple systems.

Analysis was conducted through simulation of a university campus based case study, comparing the potential of real-time and predicted data availability of local energy demand and renewable generation to reduce average carbon intensity in a local vehicle-to-grid system. The results of this analysis showed a significant difference in reduction of system carbon intensity between unmanaged charging (average fleet usage carbon intensity of 236.5gCO2/kWh), real-time rule-based V2G controls (effective fleet usage carbon intensity of 83.0gCO2/kWh) and 'ideal' predictive V2G controls (effective fleet usage carbon intensity of -445.1gCO2/kWh due to carbon saving achieved in the local building or grid). The foreknowledge provided by best-case predictive controls was demonstrated to ensure that the greatest carbon offset opportunities were utilised in the simulated system. The reduction of total system carbon intensity shows the potential for support to the grid system when predictions can be made to address uncertainty around points of energy use at both the scale of systems (renewable energy production) and the individual (per-vehicle demand).

While this paper presents the best-case for predictive control in a particular test scenario, a number of technical and operational challenges exist in the real-life implementation of machine learning and intelligent optimisation in V2G control. Systems in application must be carefully framed and designed to ensure optimum performance and appropriate handling of potentially sensitive data streams. As this study established an upper limit based on simulated perfect future prediction, real-life systems must also account for the fact that no predictive model will achieve 100% accurate prediction of factors dependent on human behaviours and therefore must be robust to prediction errors.

Given these challenges and the additional computational and infrastructural requirements of this approach to control optimisation, the question of whether the additional benefits justify the expense remains. While the findings presented show only the theoretical upper limit to such a system, it is clear that the environmental benefits of a vehicle to grid system can vary significantly depending on the rules under which the system is operated. In practical application, the upper limit presented in this paper could only be approached, not fully attained. However, the observed magnitude of difference in benefit between these two control schemes reinforces that application of machine intelligence to system optimisation is a worthwhile pursuit. Further to the specific case study of environmental benefit considered in this work, balancing competing factors such as battery preservation, minimisation of energy costs etc. is likely to further strengthen the case for machine optimisation. As additional factors are introduced and the problem of control optimisation becomes more complex, it becomes increasingly difficult for manually constructed rulesets to capture the best option in any scenario – where the implementation challenges can be met, machine learning and optimisation should provide a route towards the best case in V2G operation.

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