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Cloud-based Big Data Platform for Vehicle-to-Grid (V2G)

Florent Grée [1], Vitaliia Laznikova [1], Bill Kim [1], Guillermo Garcia [1], Matthias Wellers[1]

[1]AVL Powertrain UK Ltd., Langdale House, Sable Way, Southfield business park, Laindon, Basildon, Essex, United Kingdom, Florent.Gree@avl.com

Summary

Over the past years, Battery Electric Vehicles (BEV) are becoming prevalent. BEV can be seen as a grid load but also as a way to support the grid (energy buffering) as long as this extensive battery usage does not affect the BEV performance. Data from both the vehicle and the grid side are required, hence a cloud-based big data platform is a suitable solution to exploit these data. This study aims to develop smart algorithms which optimise different factors including BEV cost of ownership and battery degradation. Dashboards will provide key information to the different V2G stakeholders.

Keywords: BEV (Battery Electric Vehicle), Optimisation, Smart Charging, Smart Grid, V2G (Vehicle-to-Grid)

1 Introduction

The penetration of Battery Electric Vehicles (BEV) is faster than expected due to diesel emission scandal and low battery price. A KPMG report [1] highlighted that BEV will be between 11-15% of new vehicle sales within EU and China by 2025. Within the UK, the market will comprise 16-20% of vehicles over the next 10 years. Several Original Equipment Manufacturers (OEM) have aligned themselves with these projections: Volkswagen Group planned to release 80 new variants of BEV by 2025, Volvo announced that after 2019 all vehicles will be partially or completely battery-powered, and Ford will introduce 13 new BEV models over the next 5 years. There will be built-in vehicle-to-grid (V2G) capability including bi-directional charging system in the majority of BEV.

The benefit of V2G have yet to be fully explored and communicated to stakeholders – BEV owners, vehicle manufacturers, energy suppliers and government. State-of-the-art V2G technology offers various benefits. Recent reports highlight the V2G charger market will grow at a compound annual growth rate (CAGR) of 50.05% during the period of 2018-2022 [2]. Each BEV connected to the grid, could be used as a bidirectional energy storage – storing renewable energy when available and releasing that energy during peak demand. A research by Kaufmann [3], estimates the financial return from V2G could be circa $1,275 per vehicle every year; while the NREL claimed in 2015 that circa $1,825 per vehicle every year is achievable.

V2G with high BEV penetration could provide new opportunities, and threats, to the electricity market. As stated in “Electric Vehicles” IRENA report [4], there is a potential for the electricity market to adopt structures and a regulatory framework that enables V2G business models to decarbonise the grid, improve efficiency and mitigate the need for grid-reinforcement. Increased percentage penetrations of wind and solar will underpin a greater need for V2G to both optimise integration of these resources and to balance frequency disturbances created from their variability in generation. According to Navigant Research, frequency regulation revenue will reach $190.7 million by 2022 [5].

The key objective of this paper is to develop state-of-the-art V2G analysis tools and model for: 1) creating a smart data collection and management infrastructure, 2) advance analytics including charging optimisation. As data format from vehicle and from grid is different, it is important to integrate heterogeneous data format. A NoSQL database is used due to its flexibility and capability to deal with this type of data. The database is stored in the cloud in order to reduce memory and computation burden in the vehicle or the on-board charger (OBC). Based on the database stored, advanced algorithms such as route prediction, BEV range prediction and charging optimisation have been developed.

2 Vehicle-to-Grid (V2G) & Big Data

Beside the necessity of BEV data, charger and grid data are also required and play an important role. BEV have higher connectivity than conventional vehicles to alleviate range anxiety. Due to the low energy density of the battery, BEV users have concerns when the battery is reaching its bottom level and whether next charging station is available and in the proximity. Even though the number of charging station is increasing rapidly, it would be a challenge to meet rapid BEV penetration. For example, UK expects the need of a six-fold increase in BEV charging points by 2020 as there will be more than 1 million BEV on the road by then [6]. Before BEV range reaches sufficient distance or charging stations become as prevalent as gas stations, data from vehicle and charging station will play a key role in mitigating range anxiety.

These data can be stored in cloud and enriched with additional sources, such as electrical grid information and battery degradation model, for further analytics. Once the creation of the integrated database is ready, it could be used for various purposes. BEV owners, for instance, could reap the benefit of the charging optimisation by reducing electricity cost, and OEMs could use this database to understand how battery degradation would differ with various charging and driving behaviours. Charging station providers could use it to design charging infrastructure to provide outstanding service to BEV owners. For government or utility providers, this can be used to understand electricity load and to mitigate electricity load issues due to high electricity demand from BEV. Fig 1. illustrates V2G data platform and its potential users.

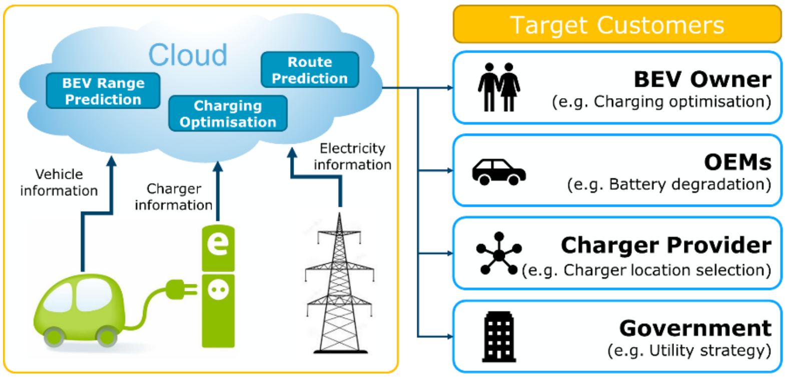

Figure1: Cloud-based Big Data Platform for V2G

3 Data Management Platform

For this research, AVL has recorded real-world data from 15 vehicles and more than 5,000 trips over 1 year. Data loggers are installed via vehicle on-board diagnostics (OBD) port, and CAN data are recorded and transferred to secure FTP (SFTP) server. These data are pre-processed in terms of data quality, consistency check and data reformatting. Vehicle information is used to create the metadata and merged with vehicle time-series data, it forms the database. This database is then enriched with electricity cost and charger information coming from external additional sources (e.g. Google API, Here API).

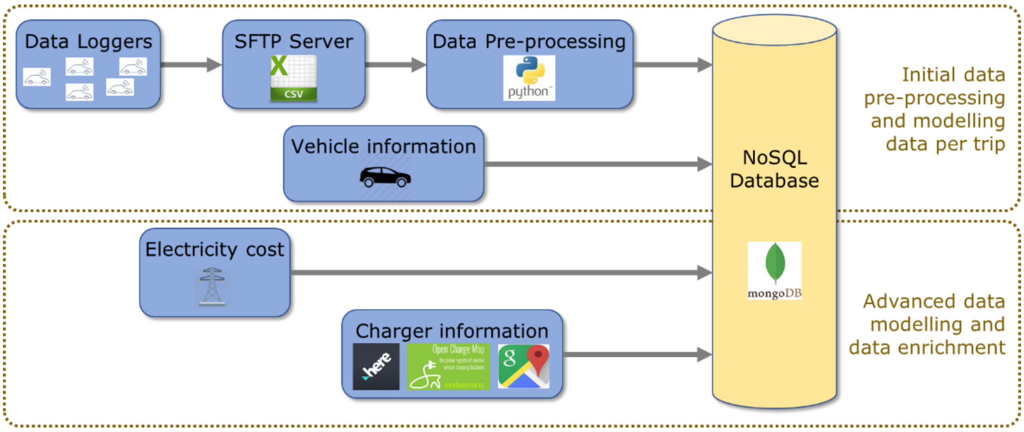

Figure2: V2G Data Management Platform

Regarding the database type, there are two options for this study: Structured Query Language (SQL) and Not only SQL (NoSQL). SQL is often used to store a relational database in table format while NoSQL is not limited to rows in table and support a non-relational database. NoSQL is schema free as it consists of documents with different formats: time-series, string and single value. NoSQL is selected for this research due to its high flexibility and scalability [7].

4 Advanced Algorithms

Once the database is ready, it could be utilised with advanced algorithms. As mentioned in Chapter 2, depending on the stakeholder, analytics may be different. In this paper, charging optimisation for BEV owners is investigated. Charging optimisation needs important information, such as next trip route prediction and next trip range, both required to set battery state-of-charge (SOC) target. Fig. 3 depicts the algorithm flow diagram where the different advanced algorithms will be detailed in the next part. The database contains all the information required to control and predict the charging power for each vehicle. The only extra input required is the Vehicle Identification Number (VIN) in order to select the appropriate data for the algorithms.

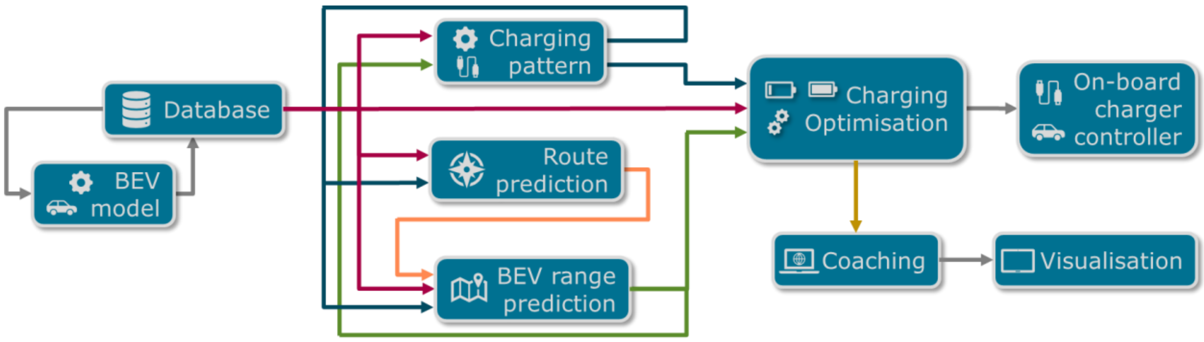

Figure3: V2G Advanced Algorithm

The data are logged from conventional vehicles, hence as part of the data pre-processing, these data need to be converted to BEV data. For this purpose, a BEV model, representing a C-segment vehicle with 24kWh, has been developed. The converted data, including battery power, SOC and average consumption, is then stored in the database and will be used as an input of the other algorithms.

4.1 Charging Pattern Prediction

This algorithm is made of two parts (Fig. 4): first the *ParkEventStopTime* is determined based on the database inputs, second the *FlagCharging* is predicted using BEV range prediction output and after running Route prediction and BEV range prediction algorithms. The objective of the first part of this algorithm is to predict the stop date and time of the parking event (*ParkEventStopTime*). The second part outputs a binary indicator of whether the vehicle is plugged in or not during the parking event (*FlagCharging*).

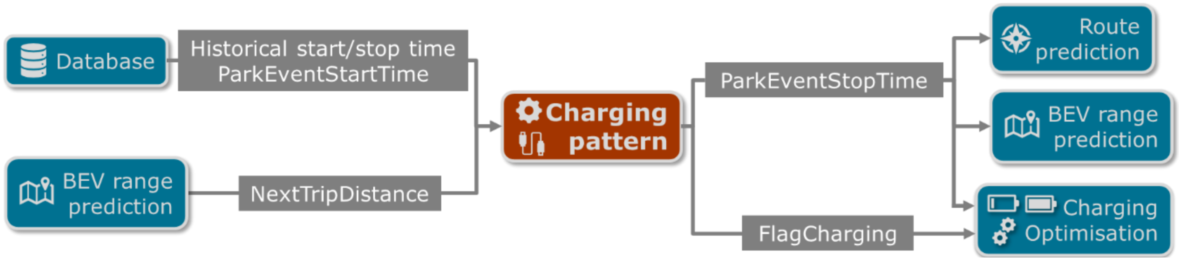

Figure4: Charging Pattern Algorithm Interaction

ParkEventStopTime is determined using the predicted duration of the parking event. This is a regression problem as the duration which is an output is a continuous value. The first step in this approach is to evaluate how influential are the inputs for solving the regression task. As previously implemented in [8], feature importance is calculated to determine the significance of the various inputs for predicting the output which is parking duration in this case. According to coefficients calculated, the most important variables are: start and stop location, start and stop time of the trip finished and binary indication of either weekend or weekday. Parking duration prediction is then tested using both Decision Tree and Random Forest.

Decision Tree is a popular and efficient machine learning approach for solving both regression and classification tasks. Random Forest is a collection of Decision Trees which randomly selects parts of data, trains Trees and averages their outcomes for the final prediction. A significant advantage of these methods is that they can both handle categorical variables. Dataset was divided into training and test set, 80% vs 20% respectively. Training data were fitted into the models which then were tested on the test set. Performance was evaluated using Mean Absolute Error (1) and by examining the correlation between real and predicted values of parking event duration.

$$MAE = \frac{\sum_{i=1}^{N} |y_i - x_i|}{N}, \tag{1}$$

Where y stands for real parking duration, x is the predicted parking duration and N is the number of observations in the test set. Results suggest that Decision Tree outperformes Random Forest according to the accuracy measures chosen. Mean Absolute Errors are 2.39 and 2.91 hours and correlation coefficients between real and predicted values are 0.65 and 0.41 respectively.

Previous research [9] examined the measure of how various factors affect user's choice of whether to charge the vehicle or not. Data examined included: clock time, location (longitude and latitude), vehicle state (driving, normal charging or fast charging), odometer, air-conditioning/heater on or off state and battery SOC. According to the results produced using multinomial logit and a mixed logit model, SOC, interval in days before the next travel day, and distance to be travelled on the next travel day are the main aspects to make the decision regarding charging. This is a binary classification type of problem, output 0 refers to vehicle not being plugged-in, 1 - vehicle plugged-in. Accuracy is calculated as a proportion of number of correct predictions to the number of all predictions. Next trip distance (see section 4.3) and parking duration are chosen to be the inputs.

The dataset used for this part of this experiment were collected from My Electric Avenue (MEA) project [10]. Those data are required as the data logged for this project do not contain information about battery SOC. Table 1 shows the accuracy results, using MEA data, provided by various machine learning methods for solving classification problems.

Table1: Charging Prediction Accuracy with different prediction methods

Method	Decision Tree	Random Forest	Naïve Bayes	Neural Network	KNN
Accuracy	80.8	85.6	83.9	85.3	79.7

According to the experiments Random Forest provides the most accurate results. Although, Neural Network's performance is only 0.3 lower, this method is significantly more computationally complex than Decision Tree. Therefore, Random Forest is chosen as a final predictor of whether vehicle is plugged-in or not.

4.2 Route Prediction

The aim of algorithm described in this section is to predict next trip destination (*NextTripDestination*) (Fig. 5).

Figure5: Route Prediction Algorithm interaction

The destination prediction has been widely studied [11] in past research. The approach described in paper detects potential destinations by examining significant locations using spatial clustering algorithm. The most challenging part for this algorithm is geographical data pre-processing. Out data consists of sequence of destinations in the form (x, y), where x - latitude, y – longitude. Therefore, the decision to use Density Based Spatial Clustering (DBSC) is made.

DBSC algorithm requires two parameters: ε – epsilon and $minPts$ - minimum number of points. The algorithm randomly selects one point (location in this case) and counts within ε the number of points. If the number of points is at least equal to $minPts$, then a cluster is formed with all these points, otherwise the point selected randomly is defined as noise. This process is repeated until all points are classified as either cluster or noise. The parameters are set by experiment as follows: $\varepsilon = 0.3$km, $minPts = 5$.

Markovian approach is a popular way to deal with problems which are based on sequential data, therefore first order Markov Chain method was used to make predictions of the next destination. Once the sequence of destinations represented as cluster numbers is formed, a transition probability matrix is calculated to represent the probability of moving from one cluster to another or to itself. The data are divided into "time-windows" as proposed in [12]. This can be justified by the assumption that a person's driving habits highly depend on the time of the day and day of the week. For example, one may always drive from home to office between 7:00 and 9:00 on weekdays. Algorithm was tested on 1,037 destinations of a C-segment vehicle. Results of our prediction algorithm can be seen on the Tables 2 and 3.

Table2: Destination Prediction Reesults for Weekday

		All	Weekday						
		n/a	06:00 - 10:00	10:00 - 12:00	12:00 - 14:00	14:00 - 16:00	16:00 - 20:00	20:00 - 23:00	23:00 - 06:00
C-seg01	# of points	1,037	189	101	78	127	293	23	9
	# of clusters	16	3	3	3	4	6	1	1
	% accuracy (2)	42	78	62.5	50	60	62	100	100
	Mean error	4.5	4.4	0.2	0.3	0.3	0.7	0.01	0
	% of error (3)	46.4	40.3	3.8	3.2	3.3	11.5	0	0

Table3: Destination Prediction Results for Weekend

		All	Weekend				
		n/a	07:00 - 11:00	11:00 - 13:00	13:00 - 16:00	16:00 - 22:00	22:00 - 07:00
C-seg01	# of points	1,037	37	46	59	63	12
	# of clusters	16	1	2	2	2	1
	% accuracy (2)	42	100	100	71	86	100
	Mean error	4.5	0	0.02	0.08	0.08	0.002
	% of error (3)	46.4	0	0.1	0.8	0.6	0

Accuracy measures used can be described as follows:

$$Mean\ error = \frac{\sum_1^N(DistReal - DistPredicted)}{total\ \#\ of\ predictions}, \quad (2)$$

$$\%\ accuracy = \frac{\#\ of\ clusters\ predicted\ correctly}{total\ \#\ of\ predictions} \times 100\%. \quad (3)$$

The predicted destination point is considered to be the centre of a cluster. As the interest is on the route prediction, mean error is more representative accuracy measure compared to % accuracy. There is only one significant error in predictions which occurs in the 06:00 – 10:00 weekday period. By detailly examining the dataset, the error mentioned is caused by a rarely driven route. The route prediction can become more accurate the more data provided.

Final step of this algorithm is to draw a route to predicted destination by sending a request to Google API.

4.3 BEV Range Prediction

The purpose of this algorithm is to predict the range required for the next trip, it requires to know the next trip distance. The next trip SOC is then input into the charging optimisation while the next trip distance is an input for the second part of charging pattern (Fig. 6).

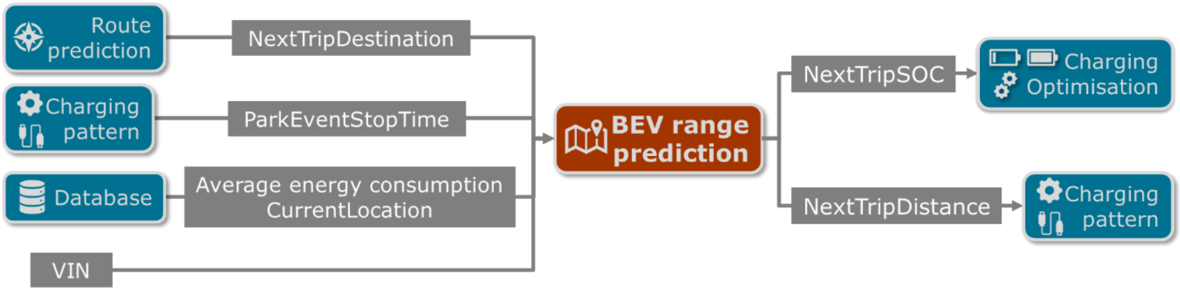

Figure6: BEV Range Prediction Algorithm Interaction

The BEV range prediction is a well-known research topic in order to accurately define the BEV range and reduce the range anxiety. The key input is the historical data. Additionally, road type, driving style or weather could be taken into account for improvement in prediction accuracy. A previous study [13] created three models: physical, energy and SOC based. For the current study, only an energy-based model is implemented. A post-processing step is necessary to calculate the average consumption versus average vehicle speed and store the trendline result in the database (Fig. 7).

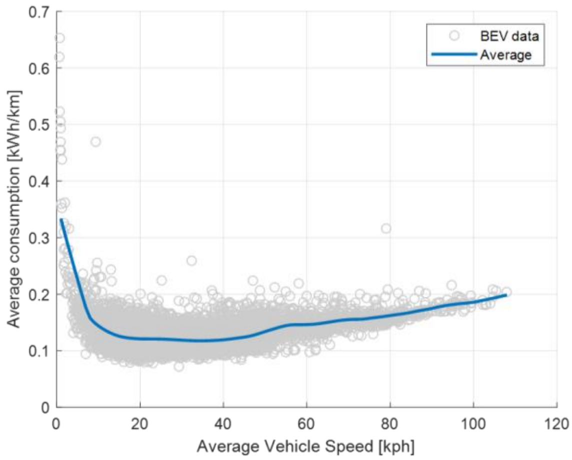

Figure7: Average Battery Energy Consumption vs Average Vehicle Speed Trendline

Knowing the next trip destination and start time and location, the next trip distance and average speed are defined using Google API. Next trip average speed combined with the trendline stored in database allows to get the next trip average consumption. The rest of the calculation is done from the following equations:

$$E_{NextTrip} = Consumption_{NextTrip} * Distance_{NextTrip} \text{ , in kWh} \tag{4}$$

$$SOC_{NextTrip} = \frac{E_{NextTrip}}{C_{Battery}} * 100\text{, in \%} \tag{5}$$

Each vehicle has its own trendline, therefore an assumption of having one unique driver per vehicle is made and the average consumption is tailored for each vehicle. This is a way to consider somehow the driving style, as an aggressive driving style leads to higher consumption as compared to a calm driving style.

4.4 Charging Optimisation

The last algorithm is fundamental, where the charging power profile is defined. The inputs are the initial SOC, the SOC for next trip, the parking duration (start and stop date time), charger power and electricity cost. All these parameters allow the charging optimisation to define the power profile with duration, cost, power and SOC constraints (Fig. 8).

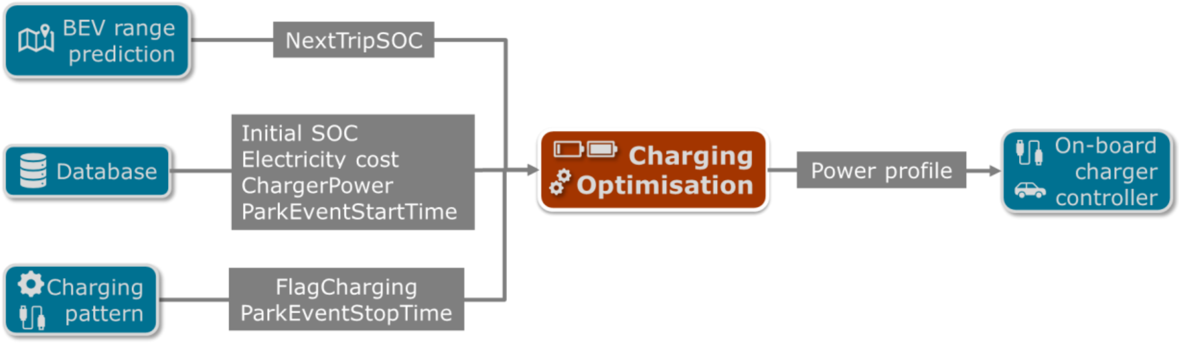

Figure8: Charging Optimisation Interaction

The charging optimisation is done using dynamic programming (DP). DP has been widely used for path optimisation and to obtain optimal SOC profile of hybrid electric vehicles [14], in this project, DP will be used to find the optimal charging power. DP runs backward and forward considering the constraints and a cost function. The cost function (6) is made of two parts: the electricity cost when charging or discharging and the battery degradation cost. Each of the parts are in pounds and have a weighting factor. The constraint is defined by the final SOC (coming from BEV range prediction, *NextTripSOC*) level that will allow to cover the next trip distance. The charger power acts as control variable where the power to charge or discharge the battery will be capped between the minimum and maximum charger power. It is assumed that all chargers are reversible, hence allowing V2G usage. Last parameter to be defined is the grid size, the bigger the grid is the better the results are but the longer the computation lasts. The grid size is fixed in order to spend around 1% of the charging event duration to compute DP.

$$J = w_1 cost_{chg/dchg} + w_2 cost_{batt\ degradation} \tag{6}$$

Where $cost_{chg/dchg}$ is the electricity cost when charging or discharging the battery. The parameter $cost_{batt\ degradation}$ is coming from the battery model where the degradation is evaluated in pounds. The modelling is based on a previous study [15].

$$\Delta_{bat}(t) = \frac{1}{Q_{bat-max}} \int_0^t |F(SoC_{bat}) G(i_{bat}) i_{bat}(t)| dt \tag{7}$$

$$F(SoC_{bat}) = 1 + 3.25(1 - SoC_{bat})^2 \tag{8}$$

$$\begin{cases} G(i_{bat}) = 1 + 0.45 \dfrac{i_{bat}}{i_{bat-nom}} if\ i_{bat} \geq 0 \\ G(i_{bat}) = 1 + 0.55 \dfrac{|i_{bat}|}{i_{bat-nom}} if\ i_{bat} < 0 \end{cases} \tag{9}$$

Where $Q_{bat-max}$is the entire life battery capacity, $SoC_{bat}$is the battery SOC, $i_{bat}$is the battery current and $i_{bat-nom}$is the nominal battery current.

Once the DP is parameterised the calculation can be run. First step, DP runs backward calculating the cost function of all the possible operation points. Second step, DP runs forward to find the lowest cost amongst the possible operation points calculated at first step. The purpose is to reach the final SOC target with the minimum cost. The charging power profile is generated and then sent to the vehicle on-board charger controller (Fig. 9).

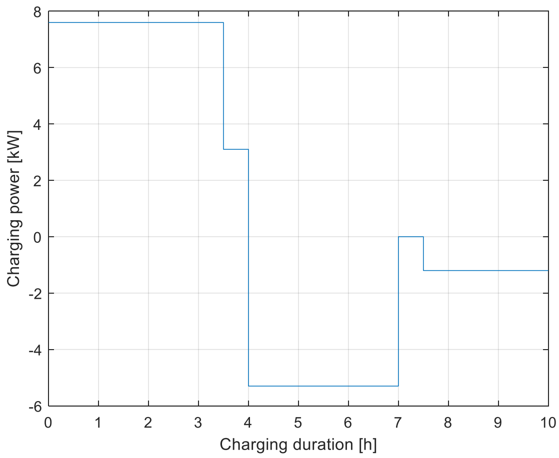

Figure9:Optimal Charging Power Profile

The electricity cost is averaged after gathering the prices from the "Big Six" (British Gas, EDF, E.ON, npower, SSE, ScottishPower). One and two rate tariffs are taken into account making the price ranging from £0.162/kWh to £0.197/kWh. There is currently no tariff when selling the BEV electricity to the grid. However, at the beginning of 2010' the electricity generated by individuals from photovoltaic panels was sold at £0.44/kWh to the grid. Based on this information, the price for selling to the grid is assumed to be from £0.25/kWh to £0.45/kWh to consider both single and two rate tariffs.

4.5 Coaching Algorithm

The previous algorithms calculate information that are useful for the driver, utilities companies and OEMs. The driver can get information about the financial benefits that could be obtained using V2G, the idea is to encourage the driver to use V2G. Utilities companies can get the charging power profile so that the production capacity could be adjusted and anticipated. OEMs can get information about the battery degradation and understand the behaviour of the battery under V2G usage. This information could be accessed on an online dashboard.

5 Cloud Platform

The algorithms have been developed on local machines before being pushed to the cloud. They can benefit from the computation power of the cloud and hence remove the need of embedded computation capabilities in the vehicle. Microsoft Azure is the cloud solution chosen. A Windows-based virtual machine is created where the database will be synchronised with AVL server database (MongoDB). On AVL server side, a python script is made to upload the database to Blob storage. Then, on the cloud the opposite process is done with another python script that downloads the database from Blob storage. The algorithms developed locally will be also run in the cloud and their outputs stored in the database (Fig. 10). The calculation outputs are analysed and dashboards are created to visualise the results. A Power BI Gateway is required in order to make the data available online. The dashboard is created with Power BI, there will be three dashboards: for the drivers, for the utility's companies and for the OEMs.

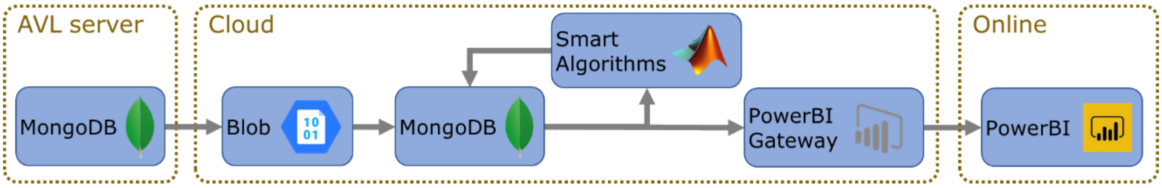

Figure10: V2G Cloud Architecture Diagram

6 Results Analysis

The assumptions on the previous part emphasize a financial benefit for the vehicle owner when using V2G. The goal here is to confirm these assumptions using real-world data. One month of real-world data have been aggregated to evaluate the benefits. Three cases have been studied: V2G with DP (case 1), no V2G with DP (case 2) and no V2G without DP (case 3). The case 1 allows the BEV owner to sell electricity to the grid and benefit from a charging/discharging optimisation thanks to DP. The case 2 considers only charging optimisation with DP. Case 3 acts as basic charging feature, battery is charged at full charger power available until either the SOC is maximum or until the end of the charging event.

As the data used are logged from conventional vehicles, it may occur that the trip distance is too long or charging event too short for the BEV battery range. These few cases are taken into account and compensated into the final cost column (Table 4). The cost column summarises the amount spent (positive) or earnt (negative) and it already considers the battery degradation cost. Case 3 is the most costly for the driver as there is no possibility to sell some electricity to the grid. Furthermore, the charging takes place at full power without considering the possibility of waiting for a lower electricity tariff. Adding the optimisation thanks to DP the driver can benefit from cheaper electricity cost to reduce the charging cost of case 2. Case 1 makes the driver earning money while making its battery available for grid support. Despite the important financial benefits, the battery is getting degraded faster.

Table4: Charging Cost Comparison for different charging system cases

	V2G	DP	Cost [£]
Case 1	Yes	Yes	-137
Case 2	No	Yes	14
Case 3	No	No	20

The battery lifetime decreases due to the extended usage, which leads to a reduction of the battery performance. The degradation weighting factor, from DP cost function, must be increased to preserve the battery. The same month of data run previously in simulation, is run again with higher values of the degradation weighting factor, ranging from 1 to 10,000. According to Han [16], the battery lifetime can be evaluated using Depth-of-Discharge (DOD) with 80% as lifetime target. This statement coincides with the OEMs warranty in terms of battery performance. Based on the initial battery cost (£3,723), the battery minimum value limit is £2,978 to ensure good performance, assuming linear degradation. A degradation weighting factor set to a value of 1 gives a lifetime of around 1 year, the BEV owner will get high financial benefits, around £2,800 for the first year, but the battery will need to be replaced much earlier than in the case of conventional battery usage. Increasing the degradation weighting factor acts as a deterrent to selling electricity to the grid, decreasing in the process the revenue from selling electricity to the grid; therefore, the degradation cost decreases and the life of the battery is extended (Fig. 11). A weighting factor values trade-off must be defined between the immediate cost benefits and the battery degradation according to the customer's needs.

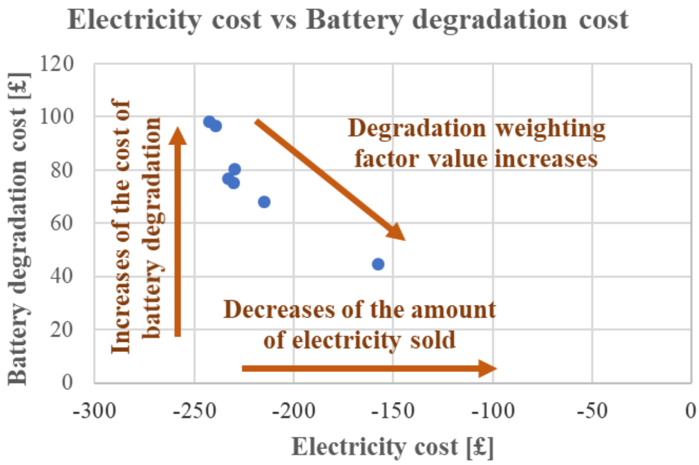

Figure11: Electricity vs Degradation Cost with varying weighting factor

7 Conclusion

This work demonstrates the potential financial benefits of V2G for the BEV owners by using their battery as an energy buffer. This energy buffer can also be helpful for utilities companies to store energy, such as renewables, and support the grid during peak time. This extensive battery usage leads to a quicker battery degradation. OEMs must consider the early degradation of the current batteries when using V2G for their future battery design. Regarding the electricity cost when selling to the grid, a trade-off must be found to satisfy both the vehicle owners and the utilities company.

As a next step, real-world data from BEV must be used to get more accurate results. In addition, real-world testing could be performed, to demonstrate the capability of these algorithms and allowing them to be improved further in the process.

Acknowledgments

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Authors

Florent Grée is a Data Science engineer in the CAE and Data Science Team. He has 6 years' experience within AVL UK and has taken a leading role in key projects including data analysis, system modelling & simulation and system engineering. He has led internal AVL R&D projects as well as commercial projects working in partnership with Ford, Jaguar Land Rover. He has a master degree in electrical engineering.

Vitaliia Laznikova is a Data Science Engineer in the CAE and Data Science Team. She graduated from City, University of London with BSc in Mathematical Sciences and MSc in Data Science. Key previous projects are within machine learning and computer vision fields. She is currently involved in Image Processing part for Connected Autonomous Vehicle project.

Bill Insup Kim is a CAE & Data Science Team Leader at AVL Powertrain UK. He received his bachelor's degree in Mechanical engineering from Seoul National University, South Korea in 2006. He has 10 years' experience as a hybrid system engineer at Hyundai Motors and AVL Powertrain UK. He has co-authored six technical papers and holds four patents in hybrid technology. His research focuses on speed prediction, driving style identification, adaptive control for electrified vehicles, optimisation and vehicle big data analysis.

Guillermo Garcia is a Vehicle Simulation Engineer in the CAE and Data Science Team for the past 2 years. He obtained a 4-year degree from Universitat Politecnica de Valencia in Mechanical Engineering. He is currently pursuing simultaneously an MSc in Intelligent & Autonomous Systems from University of Sheffield. He has been involved in projects related to the modelling and control of hybrid and electric vehicles, as well as vehicle data analysis and speed prediction research.

Dr Matthias Wellers is the managing director of AVL Powertrain UK. He is also a visiting professor of Loughborough University and a fellow of Institution of Mechanical Engineers. He is the founder of Future Powertrain Conference and an advisor to the UK government as a member of UK Automotive Council.