Parking Provision Project Proposal

Background
The Office for Low Emission Vehicles (OLEV) with the Department for Transport (DfT) are currently planning the future provision across the UK of electric vehicle (EV) charging points (CP), as part of the commitment to reducing emissions by 2050. We imagine a future where all vehicles are fully or partially electric, and every vehicle requires adequate access to a CP. Charging an EV is not as quick as refuelling a petrol engine. Different chargepoint types (slow, fast, rapid) can charge an EV partly or fully at various speeds, depending on power rating, ranging from 5 minutes to 10 hours. The demand on the electricity grid is an important consideration, and to mitigate this the majority of charging should take place at night, outside peak hours of electricity consumption (OLEV, 2011). Thus, most CPs will be domestic and located on, or nearby, the property of the EV owner.

Aim and objectives
This project will focus on informing the domestic EVCP infrastructure strategy by investigating parking provision across the UK. It is expected that properties will fall into one of the following three categories,

- Off-street parking: the property has a driveway or garage such that a private EVCP can be installed.
- Adequate on-street parking: there is enough room for all or most vehicles to park within some specified short distance of the property.
- Inadequate on-street parking: there is **not** enough room for all or most vehicles to park within some specified short distance of the property

The proportion of parking provision in each of these three categories, per local authority (LA) will serve as an essential guideline.

In this project I will aim to show proof of concept by focusing on a small number of local authority (LA) areas, for instance Ealing and Cornwall. These will provide some representation of the wide range of residential areas and the difference between urban and rural areas. The technique can then be applied over all LAs. I will also restrict my aim, in the first instance, to identifying and tagging off-street parking in residential areas.

Various high-level data and estimates of off-street parking exist that can be used to validate the outputs of this project to determine its success.

Data
The complete data for the UK are potentially large ranging from 5GB to 80GB, however with area reduced to LAs each dataset should be in the MB range. Aerial photography data could a big problem, in which I could use Google Cloud Platform (GCP) at DfT.

Data	**Useful fields**	**Access**	**Format**
Aerial Photography Great Britain (APGB)	Detailed images of UK, Low resolution: 25cm. High resolution 12.5cm is available but 4x bigger.	Free via Public sector geospatial agreement (PSGA), my colleague has access	tiff
Satellite images	Less detailed than APGB	Open source google earth and others	?
Ordinance Survey (OS) Master Map (MM) Topography layer	Unique building ID, includes property land and boundary.	Free via PSGA and already on DfT network	Geodatabase, convert to geopackage

	Pavement, street ID, heights of buildings.		
OSMM Highways layer	Road IDs, classifications, centre lines, widths	Free via PSGA and already on DfT network	Geodatabase, convert to geopackage
OS Address base plus or premium	Unique property number (UPRN), building property unit (BLPU), property type, parent address information to denote multiple residences in one building	Free via PSGA and already on DfT network	Plus is flat file
OS Open Maps local layer	Public chargepoint locations	Open source	Shapefile, geopackage
Driver and Vehicle Licensing Agency (DVLA)	Registered addresses of vehicles	DfT	SQL database, csv
Land registry	Some driveway and building ownership details	?	?
National Travel Survey (NTS)	High level off-street parking data	DfT and published stats	csv
Zapmap	Private and public chargepoint locations	DfT already purchased	csv
Traffic regulation order	Some on-street parking data; free parking, restrictions etc	May have some info at DfT already – need to contact colleague	?

Methods
There are various approaches to this problem and I have listed my main ideas below. I expect to attempt each these ideas to some extent, and possibly combine some of them. I will be using python, geopandas especially, QGIS, convolutional neural nets, and possibly some other classification techniques, such as random forest.

1. **Vehicle detection within satellite/aerial images and classification by proximity to residential features:**
   Use an existing vehicle detection algorithm, most likely neural net, to identify vehicles in an image and output the longitude and latitude of these vehicles. Then proceed to overlay these locations with the OSMM layers and to classify the vehicle as off-street parked by its proximity to a building and/or distance from the road centre line. This would be limited to the vehicles being parked at home when the image was taken, in which case the recent lockdown may be an advantage if suitable images can be found that were taken on days of less mobility, that is the week commencing 30th March, 2020. Failing that, early morning may be sufficient to ensure most vehicles are parked at home.

2. **Manual classification to create a training set;**
   To manually classify off-street parking within an image to create a training set for a neural network. The image is very different if the vehicle is actually parked there at the time or not, and if there is a garage or simply a drive. Hence the manual classification of the image may fall into three categories; garage or other covered off-

street parking, open-air off-street parking with vehicle, and open-air off-street parking without vehicle.

3. **Off-street parking detection**
   A driveway or garage is distinguished from its surroundings usually by being of a uniform colour, flat, manmade, non-green and in proximity to a building. Overlaying an OSMM layer with aerial imagery would confine the search to areas within a property boundary. Within these boundaries one could then examine the proportion of surface area that is manmade compared to green and to calculate if this were sufficient to park a vehicle on. Garages that are part of the main building may be inferred by the presence of a manmade surface leading up to them.

4. **Off-street parking potential**
   Determine the off-street parking potential of a property by looking at the building footprint, area of the front, whether there is access to the rear, and calculate if there is enough space to have a vehicle parked within the property boundary. Though this may overestimate, since a residence may have space for a driveway/garage but not choose to use it for parking, it would still be a useful figure, as an indication of potential and an upper limit to existing off-street parking. The methodology has been used by Emu Analytics and has some limitations (Emu Analytics, 2018).

5. **Classify by property**
   Take an aerial image, overlay with OSMM layer to enable grouping of the pixels by property boundary. Then for each property classify into one of either ‘has off-street parking’ or ‘does not have off-street parking’, or allocate a probability of having off-street parking.

Key literature

The course materials so far that have dealt with image processing have introduced convolutional neural nets (CNN) and generative adversarial networks (GAN), in the Learning from Data module. Much of the literature concerning vehicles and parking pertains to real time objection recognition which is not necessary here. However there are many works on detecting vehicles using CNN (Malcolm & Iv, 2018), (Tang, Zhou, Deng, Lei, & Zou, 2017). Other works exist that may also be useful in directly detecting off-street parking by distinguishing between manmade and green surfaces within the property boundary (Pacifici, Chini, & Emery, 2009) and ONS recent work on analysing the proportion of green space in private gardens (ONS, 2019). OLEV (OLEV, 2011) is included for information on the infrastructure plans. As mentioned above Emu Analytics have already tried a method to detect potential off-street parking which may be useful to build on (Emu Analytics, 2018).

References

Emu Analytics. (2018). *ON-STREET EV CHARGER REQUIREMENTS PRODUCT SHEET*.

Malcolm, W., & Iv, T. (2018). *Object Detection and Digitization from Aerial Imagery Using Neural Networks*. (August). Retrieved from https://spatial.usc.edu/wp-content/uploads/2018/09/Taff-IV_William.pdf

OLEV. (2011). *Making the Connection The Plug-In Vehicle Infrastructure Strategy*. Retrieved from www.dft.gov.uk

ONS. (2019). Green Spaces. Retrieved June 1, 2020, from https://github.com/datasciencecampus/green-spaces

Pacifici, F., Chini, M., & Emery, W. J. (2009). A neural network approach using multi-scale textural metrics from very high-resolution panchromatic imagery for urban land-use classification. *Remote Sensing of Environment*, *113*(6), 1276–1292.

https://doi.org/10.1016/j.rse.2009.02.014

Tang, T., Zhou, S., Deng, Z., Lei, L., & Zou, H. (2017). Arbitrary-oriented vehicle detection in aerial imagery with single convolutional neural networks. *Remote Sensing*, *9*(11). https://doi.org/10.3390/rs9111170

Timeline

Since this project directly benefits DfT I can devote more work time than just the 20% time protected by the apprenticeship. I have allocated 2 days a week to this project and may have capacity to allocate another half/day. Writing up of the report will continue alongside the timeline below and can also be done during non-work time.

Week commencing	Rough plan
01/06/2020	Set up python environment, solve GDAL geospatial library issues. Obtain OSMM data for chosen LAs, in geopackage format. Source relevant satellite/aerial images. Obtain access to DVLA registered vehicle data. Read through OS code on gpkg, and ONS greenspaces code
08/06/2020	Research existing vehicle detection algorithm. Read up on CNNs. Familiarise with OSMM data. Ensure data formats and libraries are compatible. Identify residential UPRNs within LAs
15/06/2020	Image processing; manual classification; segmentation into property units using OSMM topography layer
22/06/2020	CNN vehicle detection; classify vehicles as off-street parked or not
29/06/2020	CNN off-street parking detection; manmade vs green material
06/07/2020	Prepare validation data – NTS, Land registry
13/07/2020	iterate
20/07/2020	iterate
27/07/2020	iterate
03/08/2020	iterate
10/08/2020	Presentation expected to be due this week
17/08/2020	Deadline for report submission: Friday 21/08/2020

Risk management

- Acquisition of and size of satellite/aerial data: this could delay the project. I have already obtained some Aerial photography data, but it is large, I may need to use GCP at DfT. I may be able to use free satellite images which though available will require more research in order to decide which are best and learn how to use.
- Time constraints: I have another project of similar size and complexity to work on simultaneously. We also have the new term starting in September so any extension on this project would impact on that.
- Learning constraints: it is difficult to acquire so many new techniques so quickly. I do have access to colleagues and interested parties at OS who are happy to advise.

Ethical issues

There are no ethical concerns. The OS maps and APGB image data are licensed under PSGA and have therefore been scrutinised to ensure they conform to GDPR. The DVLA data would contain the count of vehicles registered to an address and no other personal or vehicle information. NTS data is anonymised and aggregated. Land registry information concerns the property and not the owner, so again, no personal information.