ME44312: Machine Learning: EV Charging Group 1*

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Contribution statement:

Group member	Portions contributed
Ian	Report writing, literature review and model validation
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Rohan	Data & feature analysis, experimentation, report writing
Willem	Report writing, literature review
Klaas	Model and feature building

Abstract. With the surge in electric vehicle (EV) use in the USA, there is a growing need to better manage Electric Vehicle Supply Equipment (EVSE), in particular during peak charging times. Efforts such as peak shaving have been known to work well at balancing the needs of the consumer (in this case charging their EV) and the load on the overall electrical grid. Various research has been done on using Machine Learning (ML) techniques in order to predict EV vehicle charging times and departures times, as an interim step towards looking at developing peak shaving procedures. This report uses a Neural Network (NN) ML model to predict how many EV's will depart a site within the next hour. The NN model parameters were varied by using different combinations of data features (including weather data), in order to increase the prediction accuracy of the model. After using a specific day to day data splitting method and using 2 methods in order to find the optimum amount of data features to add into the model, the model was used to predict the last six months of 2019 (using the 1st six months as training data). The prediction accuracy increased by almost 30% percent when using the correct data features, resulting in a 75% model prediction accuracy rate. The link between estimating the number of EV departures within the next hour and estimating the active current over time was discussed and qualitative links were created between the built NN model and possible future peak shaving applications. It was recommended that future research use a larger data set that takes into account the large dip in EV charging that occurred halfway through 2018 and then again during corona times in 2020, which caused issues for this research report.

* Dataset supplied by Adaptive Charging Network group at Caltech.

1 Proposal

1.1 Introduction

In the past decade, there has been a resurgence in electric vehicles (EV's). Being painted as environmentally friendly and having a performance closely matching that of standard combustion engine automobiles, there has been a surge in demand for EV's, thus putting additional strain on electric supply grids. This necessitates energy demand management. With the increase in computing power, Machine Learning (ML) techniques have been used to better predict electric grid usage whilst adhering to multiple constraints[9], [4] & [11]. These ML techniques help to manage the different constraints, imposed by each car owner's needs (vehicle type, amount of charge needed, duration of charging time) and various reports have analyzed those parameters. It is established by various sources that ML techniques, by in large, outperform classic time series approaches with much less computational time [6],[8] & [7]. There is not one single approach that is being used for estimating the amount of charge in EVs at a present time and also for effectively managing all the vehicles currently being charged at a parking facility, in order to guarantee that the total electrical need from the surrounding grid is not exceeded [5], [10], [3] & [2]. In addition, weather information such as temperature, precipitation, and wind can affect the power supply needed for charging EVs, which is sometimes done by lowering the power conversion efficiency (ratio of DC power supplied to the vehicle compared to the AC power supplied by the power grid) by up to 50% [18]. With the increase in EV charging, the demand on the electrical grid is getting more difficult to meet.

Peak shaving is a concept that is getting more popular, as the need to balance surging energy demand with equally rising importance for environmental concerns [14] continues to be at the forefront of public debate.
It is the case that the electricity demand varies throughout the day, with peaks occurring during the morning(home-to-work commute) and evening (work-to-home commute). Peak shaving can help society avoid the need to build expensive new power plants to meet the highest levels of demand which are needed during these peak moments, when energy is also more expensive [13] to produce. Peak shaving is a strategy that is used by an increasing amount of companies to reduce the demand for electricity during periods of peak usage [12]. It is achieved by reducing the overall demand for electricity at peak hours or by shifting some of the demand to a different time of day when there is less demand. The latter is described in more detail in the following paragraph. One method is to use smart charging systems that can schedule the charging of EVs during times of low demand and avoid charging during peak hours [15]. This helps to reduce the strain on the power grid during peak hours by charging for example at night instead of when an individual has just returned home at 6 PM. This also makes sure that the EVs are charged when needed and uses electricity when it is less expensive. Peak shaving reduces the strain on the electric power grid when it reaches its maximum threshold during peak hours and this in turn helps to ensure an af-

fordable, reliable, and sustainable supply of power to society by smoothing out the load on the power grid [17].

1.2 Goal

The goal of this research is to use ML techniques to successfully predict the number of vehicle departures (in essence departure times), given only a few input data (E.G. the starting connection time of each EV). A busy garage/parking lot located at Caltech university in southern California, USA will be used to fine-tune the ML technique. This will help future EV charging station managers and parking lot owners to think about peak departure congestion issues and help with potentially better time scheduling for EV charging.

1.3 Research Question

The use of an NN model to accurately predict the hourly number of EV departures in order to provide technical/policy guidance for garage owners regarding peak power shaving and infrastructure changes.

Sub-questions:

- Does there exist a specific pattern to which people prefer to charge their vehicles throughout the day and week?
- Do weather and temperature provide better predictive power?
- Effect of various factors pertaining to charging behaviour on the model's performance predicting hourly departures.

1.4 Scope

The model will be based on a NN learning method, using the Caltech site for 12 months (for 2019) and will involve, using the following data Table 1 (more details on how this data was compiled, are described in the methodology section) Theoretically, the time of day and day of the week of heavy charging times could be used to capture patterns in charging behavior. This information can be used to estimate the total power demand and to predict whether the charging station will exceed its maximum current limit. Note that the Caltech site is comprised of 54 EVSE's and data for all the EVSE's will be used.

This report will not look into chemical properties of batteries in EV vehicles, although there is sufficient literature on the difficulty in accurately predicting the state of charge of each EV battery. [1], [2]

2 Methodology

2.1 Data set preparation and analysis

The analysis presented in this report relies on two primary data sets, namely ACN (Adaptive Charging Network) data and weather data. These data sets

Table 1. ACN and weather data parameters for Neural Network

Parameters	**Units**
Weather(Daily)	
Temperature Wind Speed Precipitation	Degree Farenheits Knots Inches
User Inputs	
kWh-Requested miles-Requested Minutes available	kWh miles minutes
Charging usage parameters	
Connection time Charge complete time Disconnection time	Hour, minutes, day, month, year

consist of a lot of diverse information that will be explained in the subsections below and which had to undergo data processing before data analysis.

ACN data The types and descriptions of the fields involved with the ACN data are shown in Tables 2 and 3, for general fields and user inputs respectively. In this section, the selection criteria describes specific fields and how they were modified to meet the analysis requirements. Additionally, this section covers the data processing and analysis that was employed to understand the data in the study.

– Since the focus of the report was specific to the Caltech location, fields '_id', 'sessionID', 'stationID', 'timezone', 'userID', 'clusterID' were removed from the data set as it does not provide additional information for the analysis.
– The data set contains empty values for the 'donechargingTime'. Deleting such data points can cause discontinuity in the analysis as the research compares the number of cars that left at a specific moment in time with the number of cars that left an hour/day/week ago. Therefore, these empty data points were replaced with its corresponding 'disconnectTime'.
– The use of time, which was used to know the moment of connection, disconnection and done charging, is critical to the analysis. Therefore, getting the time in the right format, is essential. Hence, 'c_time' and 'd_time' show the connection time and the disconnect time in minutes in order to realise the time of connect/disconnect with respect to the day. Furthermore, 'c_epoch_time' and 'd_epoch_time' were established to get the time in Unix time format.

Table 2. Field types and description for ACN data

Field	Type	Description
_id	string	Unique identifier of the session record.
clusterID	string	Unique identifier for a subset of EVSE's at a site, such as a single garage.
connectionTime	datetime	Time when the EV plugged in.
disconnectTime	datetime	Time when the EV unplugged.
doneChargingTime	datetime	Time when of the last non-zero current draw recorded.
kWhDelivered	float	Amount of energy delivered during the session.
sessionID	string	Unique identifier for the session.
siteID	string	Unique identifier for the site.
spaceID	string	Unique identifier of the parking space.
stationID	string	Unique identifier of the EVSE.
timezone	string	Timezone of the site. Based on pytz format.
userID	string	Unique identifier of the user. Not provided for sessions which are not claimed using the mobile app.
userInputs	list	Inputs provided by the user. Since inputs can be changed over time, there can be multiple user input objects in the list.

Table 3. Field types and description for user inputs in ACN data

Fields	Type	Description
WhPerMile	float	Efficiency of the EV in Watt.hours per mile.
kWhRequested	float	Energy requested by the user in kilo-Watt.hour.
milesRequested	float	Number of miles requested by the user.
minutesAvailable	float	Length of the session as estimated by the user.
modifiedAt	datetime	Time this user input was provided.
paymentRequired	bool	If the user was required to pay for this session.
requestedDeparture	datetime	User estimated departure time.
userID	string	Unique identifier for the user.

Weather data In addition, temperature, precipitation and wind speed data were also collected, via a fellow university [16], for the same time period. This weather data was part of a larger weather data set but it is simplified in order to reduce the file size. It is used in the NN method to increase the accuracy prediction and in the use of weather data in order to predict fluctuations in energy demand and charging finish time. Similar operations were done to the time stamps provided in the weather data so a link could be made between the weather and ACN data, using the epoch time.

2.2 Data features

Data variables are created to better predict the number of vehicles leaving in the next hour. These features are shown in Table 4 below:

Table 4. Generated data features

Feature name	Description
connectionTime	Split into multiple columns suggesting the day of the week, the month of the year and time of the day. These are designed to help with understanding the correlation between the number of cars leaving in the next hour to the various features.
n_left **(Target variable)**	Represents the number of vehicles that leave in the next hour with respect to the connection time of a specific data point.
cars	Represents the number of vehicles that are currently on the parking spaces. This is calculated with the help of the 'c_epoch_time' to find the cumulative number of vehicles in that time period.
n_done	Represents the number of vehicles that are done with charging but are still at the parking site at a specific moment in time. This is checked by checking whether the 'done_epoch_time'(done charging time) is less than the 'c_epoch_time' and whether 'd_epoch_time'(disconnect time) is greater than 'c_epoch_time', of the data point under consideration.
cars_last_hour	Number of vehicles that left in the previous hour.
n_left_last_week	Number of vehicles that left in the previous week.
time_sum time_mean time_median time_min time_max	Gives the sum, mean, median, etc of charging times of the vehicles that are already on the spots with respect to the arriving vehicle. The time_median was found to be the most useful parameter to predict the number of vehicles departing.
User inputs	To understand if the user inputs of minutes available have a relation with the actual number of leaving in the time interval.
Weather data	Weather information is added to the same time periods of the data to check if the weather aspects such as rain, wind and temperature have an impact on the prediction of the number of vehicles leaving in the next hour.

These data features apart from the target variable allow this research to optimize the model predictions by selecting all or only certain data features to be present in the model. Different combinations were expected to produce different score values for predicting the target variable.

2.3 Model selection

This report choose to focus more in depth of an NN model since it has a couple of advantages:

- It can do unsupervised and supervised ML techniques, namely getting at the non-linearity in data sets which were found to be present in EV charging data.
- NN models also allow to test different activation functions within the hidden layer (different neurons), such as logistic regression vs a sigmoid function in order to find the best fit the EV charging data.
- Due to the output layers in an NN model being after the hidden layers, it can create predictions by using a softmax logit activation function.

For the purposes of this research, a NN model using MPLRegressor was chosen using multiple parameters as predictor variables in order to predict n_left (dependent variable–number n of cars that are leaving within the next hour). The score() method of the MLPRegressor class returns the coefficient of determination R^2 of the prediction, which is a measure of how well the model fits the data. The R^2 score can range from negative infinity to 1, where a score of 1 indicates a perfect fit and a score of 0 indicates that the model always predicts the mean of the target variable.

2.4 Final model adjustments

In order to use a NN model, the data 1st has to get filtered in order to be scaled properly. Certain information was also removed in order to increase the prediction accuracy of the model, whilst still providing enough information for and keeping computing times short. Notably N_left_last_week was created as mentioned in Section 2.2 above and it serves as the main predictor variable. Moreover, it was noticed that the predictor predicted negative number of vehicles which caused inefficiencies in model. Therfore, a function *'relu()'* was created to modeify these negative values to zero. In addition, data splitting needs to occur so that the model is trained on the data and can then be run comparing itself with the test data. 6 months was chosen for each the testing and the training data.

Data splitting A feature of NN models is that the data is split into a training data set and a testing data set, so that the best matrix to minimize the loss function, related to predictions of departure times, is found. One method is simply setting the start- and end training dates (with the time period after that until the end of the year being the testing data). There is a disadvantage to this procedure, being that the model doesn't have any training data for a certain period of the year, which can cause the model to under-represent school holidays and other seasonal fluctuations (e.g. in December with the winter holidays/ school break).

The other method is day splitting. It allows to avoid the irregularities from a significant shift in the number of vehicles if the data was randomly split over the full year. Day splitting is where for every 2 training days, the next day would go to the testing data data frame. This research looked at three timelines for day splitting: 2 training days for 1 testing day, 3 training days for 1 testing day and finally 4 training days for 1 testing day. These three options were chosen so that there was variability over the days of the week and between months for the training data set.

Data feature selections Another final model adjustment that was made, was selecting appropriate data features in order to best calibrate the model. As shown in Figures 5 & 6 in the Appendix, a form of heuristic is adopted where 3 NN models with different layer and neuron configurations were run for all the data features individually in order to assist in the selection of the features chosen for the final model. What is shown there are the 10 highest weights of each data feature in the 1st layer for different models and how they influence the final model output. Then the common features with the highest weights (absolute values) across all models can be chosen(marked in red) while any features related to the target variable(marked in yellow) should be excluded. The remaining features can also be added should it improve the model accuracy in the subsequent layers. It is difficult to get weights for each data feature from the deeper hidden neural layers of the NN model due to the implicit connections that are created between these layers and respective neurons. Other ways of selecting the appropriate mix of data features involve algorithms and other heuristics. This heuristic was not adopted further but is rather used to verify the feature selection algorithm discussed next. The list of features chosen by this heuristic closely match that to the one selected by the algorithm with some difference in one or two selected features.

In addition to the above-mentioned manual check of the data feature weights, a feature selection algorithm was also used in order to look at all the parameters and make trade-offs on model fit and what features would best allow the model to fit to the data. The algorithm creates a data frame that contains the R^2 value for each individual feature, as well as the Pearson correlation coefficient between each feature and the target value.

Next, the algorithm selects the top 10 features with the highest R^2 values and the top 10 features with the highest absolute correlation with the target variable. It then checks for correlations among the selected features and removes any features that have a high inter-feature correlation. This results in a list of features that have the best combination of high R^2 scores, high Pearson correlations, and low inter-feature correlations.

The algorithm finally calculates the R^2 score for all features in the list and stores these scores. The feature with the highest score is saved, and the algorithm starts over, but this time with the new R^2 scores being calculated in combina-

tion with the saved feature. The algorithm stops when it reaches the maximum number of features or when the score does not further improve (via simulated annealing).
For the feature list, the following one's were found to have the most effect on the model: ['c_time', 'late_counter', 'interval_counter', 'cars', 'n_left_last_week', 'time_med', 'Total_request', 'time_min']

In the following section, a small K-means clustering was performed to briefly describe the heterogeneity of the EV car owners and the results of the various NN model runs will also be shown, with the 2019 data for various data splitting methods.

3 Results

3.1 K-means clustering–descriptive statistics

A K-means analysis was done to understand an initial pattern in the behaviour of the people with respect to their charging habits. The clusters are formed based on common characteristics that are involved within the data set and are used to identify the characteristics that are unique to them.
Performing the Elbow Method as shown in Figure 1, a K-value of 7 was considered reasonable and the results obtained are as shown in Table 5.
The clusters demonstrate that there were no clear classifications of the clusters. This K-means cluster analysis did not reveal any distinct characteristics of

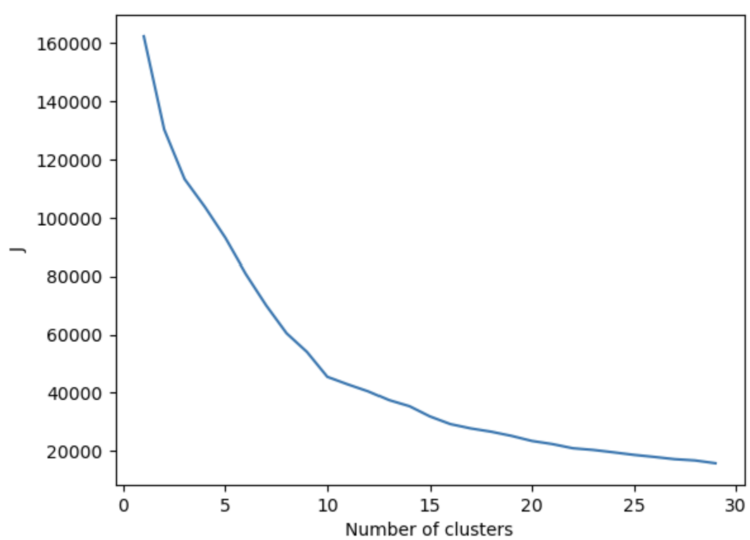

Fig. 1. Elbow method

charging at a specific time or day of the week. The results revealed that there were some outliers in the data set that made up 11% of the data set and deviated from the clusters' general routine. The vehicles in these clusters(2 and 5) appear to have a lower average charging time but a higher average time of being connected when connected at night or in the morning.

Table 5. K-means clustering results (# of clusters chosen per elbow method: 7).

Cluster	**Size (percentage)**	**duration (minutes)**	**kwH delivered**
1	18.66	379.99	8.74
2	4.90	297.31	11.44
3	19.10	367.18	8.21
4	17.79	368.71	8.17
5	6.24	284.98	10.00
6	15.73	379.97	10.28
7	17.58	370.78	8.68

3.2 NN model results

The results of the various NN models changed as more data features were added or removed. Table 6 shows the 5 different NN model runs that were made, along with their respective predictive accuracy (R^2) and mean absolute error values. Note that Table 6 consisted of performing numerous various data feature selection sources (ranging from 3 up to 7 data features) and both data splitting methods mentioned in the methodology. As such, the model mean absolute errors and R^2 values may have been higher even when a model run had less data features. As shown in Figure 2, the range of EV's that were predicted to leave within in the next hour was from 0 to 23 vehicles. The relationship between c_time and vehicle information is fairly strong but as was found in the results, epoch time had a very low correlation with the data (possibly due to it is cumulative nature).

Table 6. Prediction accuracy and model parsimony.

Trial number	model change	score (R^2)	mean absolute error
1	Original with only connection time	0.59	36.36
2	with limited data features (max 5)	0.73	0.78
3	with weather data	0.73	0.81
4	**with user inputs and model generated 1-week historical data**	**0.75**	**0.70**
5	with monthly and weekend data	0.72	0.75
6	with KwH delivered info	0.71	0.80

In addition, the model looked at adding user inputs and months of the year in order to better predict when the users. The model run in bold in Table 6, used the day splitting in order to get a confidence interval for the R^2 of [0.745, 0.762].

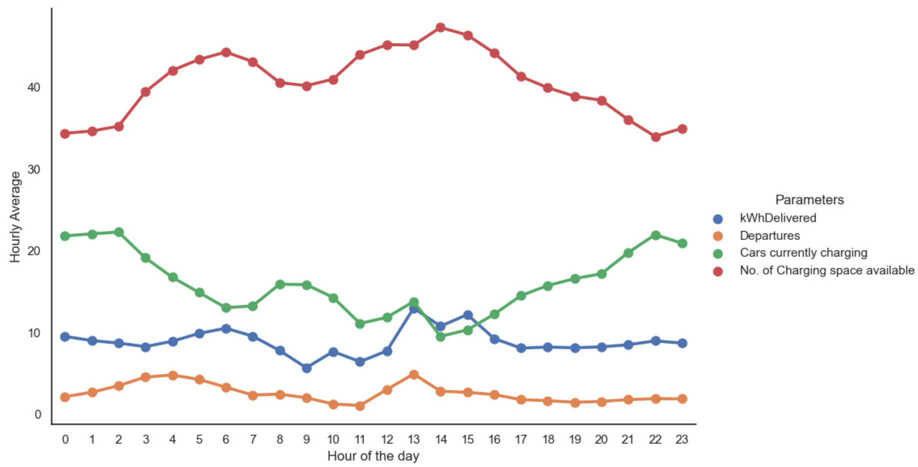

Fig. 2. Data mapping for KwH delivered or amount of vehicles over a 24 hour period

Overall, Figure 2 shows a couple of trends. There are visible peaks where vehicles enter the garage and are charging, which are in the AM (9AM to 10AM) and then also a steady increase in the evening after 5PM, showing local residents in the area and students that may be parking their vehicle overnight. The area around the parking garage consists of a fairly dense residential environment, which accounts for the large duration times seen in Table 5 and shown in Figure 2.

4 Discussion

As the previous section shows, a NN model that is properly trained and has a good set of data features, can fairly accurately estimate how many vehicles will be departing the garage within the next hour. The project team started by trying to use more data (April 2018 through January 2021) in order to get better NN model results, however, it was observed that there was a large drop in vehicle use starting in November 2018 as shown in Figure 4. This caused issues with the NN model in accuracy prediction and also caused the score values to be negative. This was due to the inappropriate scaling and data quality which was triggered by the sudden drop in the number of vehicles using the Caltech facility. The reason behind this drop in vehicles is intriguing since it was not a seasonal drop (due perhaps to school or the site not being active during the winter holidays) and lasted for all of 2019. Data from 2020 onward was also not used since COVID negatively affected travel patterns for the Caltech site.

Also at the beginning of this research, the current of electric was to be tracked at any given time to see where the daily peaks of energy consumption were. However, as shown in Figure 3, no clear peak threshold was uncovered. In addition to that, the charging system was already reducing the mean current (green line) from 1 EVSE once other EVSE's were in service, in an effort to minimize the overall cumulative current needed (it appeared to already be peak shaving).

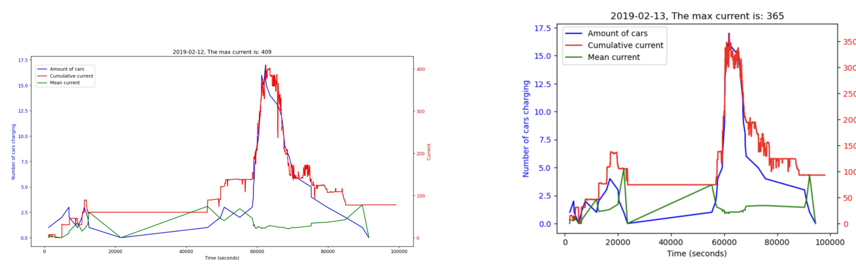

Fig. 3. Caltech-EV current data & vehicle data by second for 2 days in February 2019 (12th and 13th)

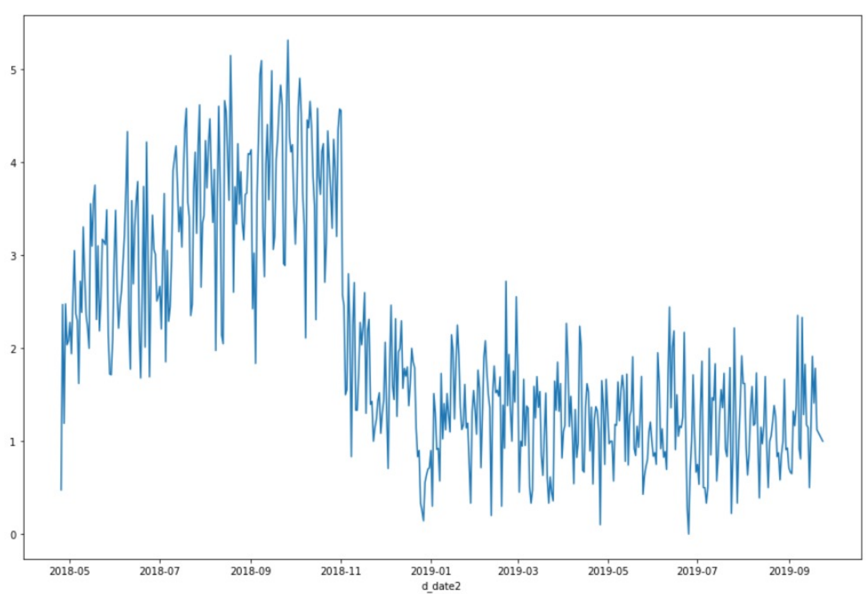

Fig. 4. Caltech-EV number of vehicles charging by day for the original data set

Finally, the data collection and scrubbing process required that each day was retrieved separately, which made predicting on a monthly- or yearly time-frame extraneous. Further research could be done at this level of granularity in order to look into the second by second variations in the current and propose optimization methods at that granular level. This is useful since it will predict the future energy required in addition to ultimately reaching the prediction of the interaction between number of EV's, charging time, and energy usage. More information regarding the relationship between current (chargingCurrent) and the number of estimated departure vehicles could be further investigated in order to further improve the NN model studied.

5 Conclusion

This research started by looking to see if predicting the state of charge of EV's would allow the project team to make conclusions and recommendations regarding efficiencies that could be made regarding energy peak shaving. However, due to the complexities of gathering the data in a time efficient manner, this report refocused efforts into looking at how a NN model can accurately predict the number of EV's departing the garage within the next hour.

The following questions were used in order to respond to the main research question:

- *Does there exist a specific pattern to which people prefer to charge their vehicles throughout the day and week?*
- *Does weather and temperature provide better predictive power?*
- *Effect of various factors pertaining to charging behaviour on the model's performance predicting hourly departures*

Although the current analysis was useful in predicting the number of departures in the next hour based on the number of cars that left in the previous hour/day/week, no definitive characteristics in people's behaviour were discovered since no personal information was available to differentiate who owns which EV vehicle (professor, student, or local resident). However, Figure 2 does allow some qualitative trends to be made when looking at a typical day, such as EV's leaving the garage in the early morning (4 to 6AM) followed by them returning to the garage between 3PM until 10PM). Weather and temperature data features did not prove to have an effect on the model fitting, as shown in Table 6.

The data features and data splitting options implemented in this study, proved that a NN model can accurately predict hourly EV departures, which allows garage owners to better gauge when their peak congestion times will be. Infrastructure changes such as an additional exit lane could be installed (or converted from an entry only lane to be dual purpose). In addition, as was mentioned in the discussion, future research can be performed in order to link EV departures with peak current delivered in order to assess how peak power shaving could impact operations and EV charging time.

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6 Appendix

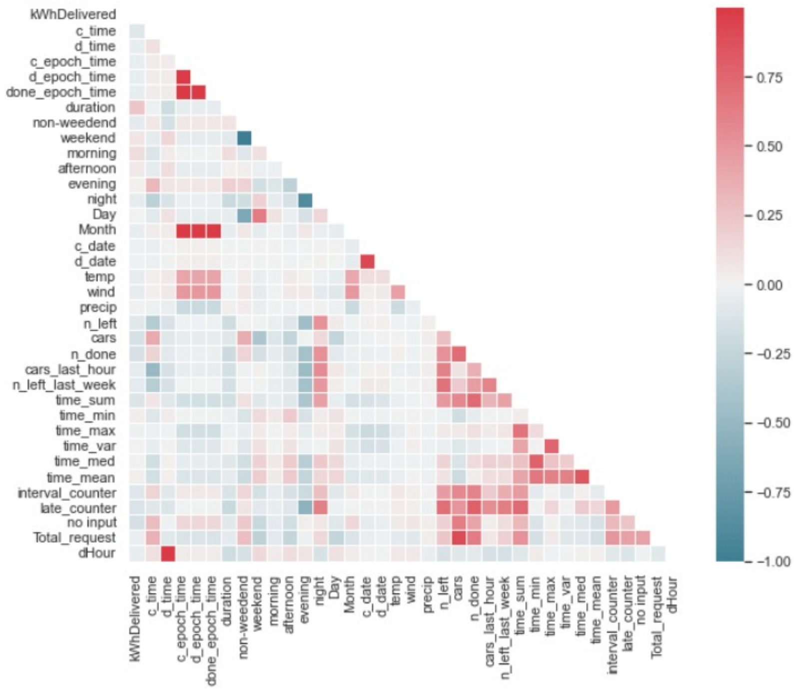

Fig. 5. correlations matrix for data features

Neural Network configurations					
1 layer 1 neuron		2 layers (1st: 1 neuron	2nd : 100 Neurons)	3 layers 1st: 1 neuron,	2nd and 3rd : 100 Neuron
Parameter	Weight	Parameter	Weight	Parameter	Weight
non-weekend	2.820036006	late_counter	2.566225971	time_min	2.393164852
late_counter	2.75625391	morning	2.206999981	late_counter	2.373073467
weekend	2.55735065	time_min	1.917191038	morning	2.207016522
Month	1.853493555	weekend	1.64457238	weekend	1.779950587
n_left_last_week	1.226889256	afternoon	1.634001267	Month	1.775265743
done_epoch_time	1.205353726	Month	1.602853701	non-weekend	1.539222631
interval_counter	1.190082153	non-weekend	1.4415613	c_time	1.4553803
cars_last_hour	0.868092849	c_time	1.340017285	interval_counter	1.129617532
c_time	0.685913684	interval_counter	1.151128662	afternoon	0.920032108
no input	0.680223544	cars	1.071890295	done_epoch_time	0.908590727

Fig. 6. Data feature selection weights
(Common features(red) should be chosen while target variable features(yellow) needs to excluded