USING LIGHT ELECTRIC VEHICLES FOR V2G SERVICES IN THE ARCTIC

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ABSTRACT

The proposed paper documents research carried out in the Smart Charge project. This project has investigated the use of electric snowmobiles for V2G purposes. Electric snowmobiles and ATVs have been introduced in remote areas in the Arctic to replace the fossil fuelled vehicles that dominate today. Electric versions of these can add extra loads to the local electricity grid. But they can also be considered a resource for energy flexibility. The Smart Charge project is in the process of developing a concept that can support the management and control of a set of snowmobiles for V2G services in the Arctic. An essential part of this is prediction. Creating the necessary foresight is important, to mobilize, prepare and to engage such vehicles to provide peak shaving assistance for a grid. The project has investigated different methods for this and has addressed the practicality of the approach developed for a use-case set in a part of Northern Finland. The paper concludes that V2G services with snowmobiles can be feasible and well supported by the prediction methods applied. The findings also suggest that the approach developed could be generally applicable, not only in the Arctic.

INTRODUCTION

In arctic areas such as northern Norway, Finland, Sweden, Canada, Alaska and Svalbard, mobility today is very much dominated by light vehicles such as ATVs (all-terrain vehicles) and snowmobiles. Most of these vehicles are fossil fuelled. However, recently electric versions of such vehicles have been introduced in the commercial market. Assuming that light electric vehicles (LEVs) like these are going to a gain a solid foothold in these regions, like electric cars have done already in some parts of the world there will be an impact on the grid system, but possibly also a way to manage loads in local distribution grids and microgrids. LEVs need to charge, but at the same time LEVs could possible represent a resource and provide energy flexibility services to handle capacity issues or function as an energy reserve to improve supply and increase supply resilience. With the introduction of LEVs in these regions new opportunities arise based on the vehicle-to-grid (V2G) concept. In comparison with buses, trucks and cars a single LEV has a limited battery capacity to offer. An extensive fleet of LEVs would be needed to create a practical option. But there exists some favourable possibilities. The population of LEVs in the arctic regions may be dense compared to the community that they serve. In the case of Longyearbyen at Svalbard with a permanent population of a little more than 2000 people there exists approximately 2300 registered snowmobiles. The Arctic is subject to dramatic seasonal changes. This entails distinct cyclical use or non-use of the vehicles. For instance, during the period late April to late October, the snow conditions are very poor or non-existent, making the snowmobile useless as a means of transportation.

Consequently, snowmobiles are typically parked idle during the summer period at Svalbard and in other places in the Arctic. Due to the limited physical size of LEVs, it is possible to park a significant number of vehicles in a limited area. Hence, a summer based V2G regime based on electric snowmobiles could be established with lesser constraints than vehicles in all year use. During winter a V2G concept for snowmobiles would face similar challenges to that typically considered for electric cars in urban areas. The research done in the Smart Charge project has been concerned with these issues, and the project can offer novel insight regarding the basic requirements that need to be considered in order to provide a useful V2G service by means of LEVs in the Arctic. Due to the relatively small battery units installed on electric vehicles a considerable number of vehicles need to be engaged, managed and controlled. This in turn requires certain provisions that the project has identified and tested. The scope of the project has been limited to first generation, electric snowmobiles. However, we believe that a big part of what has been established is relevant for LEVs in general and even for V2G regimes based on larger vehicles. V2G must involve advance notices to prepare the vehicle and inhibit other use of it. During the winter this is especially important since the snowmobiles are in regular use.

STATE-OF-THE-ART AND RELATED WORK

The research presented here extends previous documentation in the project [1]. During the recent years a lot of buzz around V2G has been witnessed, increasing in intensity with the growing number of electric vehicles and an expanding charging infrastructure [1]. In the wake of this a polarized debate arose whether the benefits of V2G could balance out the disadvantages. Sceptics have

Table 1 Two different models of electric snowmobiles available in the market today

	Model 1	Model 2
Battery capacity li-ion (kWh)	23kWh	7-21kWh
Battery peak power	67kW	60kW
Charging rate – onboard charger	Up to 6.6kW AC	Up to 6.6kW AC
Charging ports	Type 1-CCS	Type 1-CCS
Top speed	100 km/h	100 km/h
Range	140km	100km
Weight (kg)	341	270
Price	From $15,000	From €15,000

primarily been concerned with battery degradation. A discharge pattern involving transfer of power from the vehicle's battery to the grid or as a behind-the-meter resource for buildings were believed to cause loss of value for a vehicle owner that could not be defended economically. Others expressed concerns that a viable business model for V2G was lacking. The proponents had a different opinion and Nissan was an early mover. The CHAdeMO protocol offered a V2G opportunity and most early V2G trials typically involved the Nissan Leaf model. However, no open standard, supporting Type 2 and CCS connections became available before the introduction of the OCPP version 2 protocol. Even today, few car models have adopted the ISO 15118 which is essential for communication between the electric vehicle and the external charging infrastructure and required for both Pay and Charge services and V2G. The INVADE project adopted a systematic approach to establish essential provisions for practical Smart Charging as well as V2G.
Issues and opportunities mentioned have been addressed by [2-7]. The work reported here has extracted and extended insight presented in these references. However, the vast majority of these have focused on V2G services for electric cars. Documentation of industrial initiatives that have adopted V2G for larger vehicles such as buses have also been documented [3]. However, no other project, to the authors' knowledge, have addressed the creation of V2G services with LEVs and definitely not any research addressing electric snowmobiles and, the Arctic in particular. One apparent reason is that the history of electric snowmobiles is a very recent one, triggered by green shift policies in Europe as well as in North America. But the recent market introduction of such has triggered considerable interest. For the project, snowmobiles with the specifications shown in Table 1 have been subject to the work documented.

THE SMART CHARGE V2G CONCEPT

To establish a practical V2G service a number of snowmobiles need to be managed and the individual power contributions need to be aggregated. Despite the differences between summer activities and winter activities the snowmobiles can be grouped as shown in Figure1 as a nested Boolean sets, the Venn diagram shows the different groups as sets and subsets. This

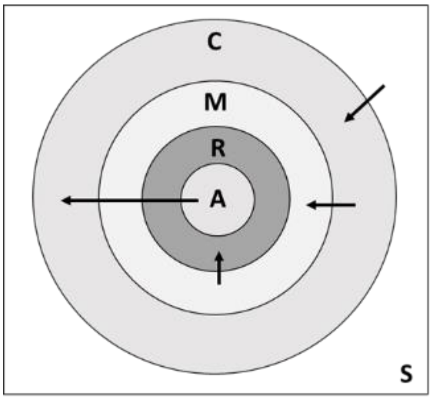

Figure 1 A LEV based V2G fleet can be organized as nested sets. A: vehicles activated. R: vehicles needed for the whole curtailment period, M: The total number notified and mobilized in some way for an upcoming V2G session. C: The full group of vehicles under contract. S: all vehicles.

categorization is important. It helps to determine the size of the fleet of snowmobiles required to counter an anticipated peak. In addition it defines different states for management and control that requires early notice and lead time for mobilization, completion of the required fleet to be engaged and more. Beyond all it provides a basis for information for owners of the vehicles in due time. Expectation management in V2G regimes is important.
The set S refers to all registered snowmobiles within a community or area. C refers to all registered snowmobiles under contract with a V2G-regime. M is the set of snowmobiles that need to be mobilized by means of an early notice and await further instructions. R is the minimum set of such vehicles required to produce the power to sustain peak curtailment as long as demanded. A is the set of vehicles which are activated and contribute to a feed into the grid. The reason that R>A is because batteries in snowmobiles are small. To last through a whole peak shaving period a replacement needs to be established and activated when the batteries of first A-group are depleted or have reached a predefined minimum state-of-charge (SOC). The arrows in the diagram serve to illustrate a migration between the sets. When the SOC has reached a minimum, a snowmobile needs to be dismissed and another must take its place, if the overall discharge action is not terminated. Replacement candidates in R will then be engaged. Group M are essentially standby and will not be engaged unless predicted capacity requirements proved to be wrong, a technical problem arises or violation of the contractual agreement occur. Throughout we assume a contract that specifies a subscription fee and an activation fee as well reimbursement of discharged energy. In addition, we suppose a penalty fee for contractual breech [8]. An arrow points from C to M and suggests a transfer when replacements for members initially mobilized must take place.
Circumstances may inhibit an owner of a snowmobile to take part and we suppose that the contract defines a maximum number of rejects within a contractual period to allow members of the regime to dismiss a call for mobilization. We also assume that recruitment to the V2G

regime is ongoing and that there could be a growth in C. It is important to understand that the arrows drawn involve different time constraints too. In our work we have considered the following: $t_{RA,} < 1 seconds,\ t_{MR} < 1 hour,\ t_{CM} < 1 day$ and t_{SR} can be measured in weeks. When snowmobiles are parked idle during the summer these time constraints are less important as the snowmobiles are already stationary and would be connected. To build a large enough V2G fleet and have the different vehicles pass through the different states time is essential. The time limits associated with the different state transitions are dependent on the peak shaving strategy, the extent and duration of the power peaks anticipated and the magnitude of the reduction that will be specified in the contract with the grid owner or his representative.

The Smart Charge project has dedicated much of its effort to solicit tools and methods to support the V2G management concept for snowmobiles. It is crucial to create the best outlook for mobilization as well as rolling engagement. The rest of the paper will address this part specifically.

METHODOLOGY FOR FORECAST AND DEVELOPMENTS

For aggregated capacity considerations the data on the snowmobiles in Table 1 were applied. To support the concept described above with sufficiently precise forecasts and the defined use-cases, different machine learning methods were applied and compared with the required forecasting. The ambition was to find a solution for both short-term predictions and create models with sufficient prudence to support the forecast for more extensive periods forward. Load data used for training and testing was collected from two different sites in the Arctic region. One of the use cases in the project related to the situation in Longyearbyen. However, the use-case described, which has also been addressed in [1], stemmed from a recreational site not far from Rovaniemi in North-Finland. The site in Finland provided load data with an hourly resolution that originated from two substation areas, Lumikartano and Iglut. Several machine learning models were subjected to the dataset originating from these sites. This was needed to determine the most suitable approach for our purpose; Extreme Gradient Boosting (XGBoost) method [9], and deep learning methodologies such as Deep Feedforward Network, Deep Convolutional Neural Network (CNN), Recurrent Neural Network Long Short-Term Memory (LSTM) model, and Auto-Regressive Recurrent Neural Network (AR-LSTM) models [10]. The methods were applied for short-term and long-term predictions in light of the conceptual management model described above. The load data was also analysed to determine peak occurrence and likely peak recurrence to determine capacity requirements and fleet size.

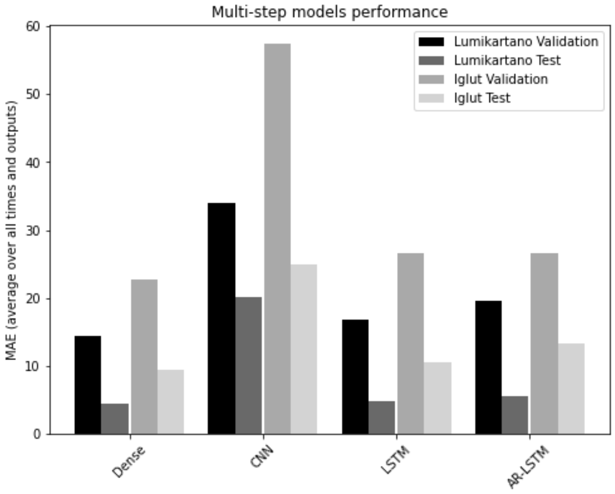

Figure 2 The benchmark of the models performance for long-term predictions.

Table 2 XGBoost model performance for short-term predictions of the two sites.

Site	MSE	RMSE	MAE
Lumikartano	107.470	10.364	5.330
Iglut	129.586	11.384	5.888

RESULTS

For short-term predictions (1 hour horizon) XGBoost proved to be, by far, the best candidate in test. Multiple validation and test exercises proved that this decision tree based boosting method was better than all the other neural networks-based models listed above. The XGBoost model carried out the forecasts with a lower error rate and better accuracy in predicting the consumption peaks. Note too from Table 2 that the Mean Absolute Error (MAE) is less than 6kW, which suggests that a tolerance measured in terms of number of actively engaged snowmobiles is less than 2 vehicles.

We monitored the performance of the models for both short-term and long-term predictions. However, it is important to note that the models' performance alone on training data does not imply the practicality of a model. Indeed, it is of great importance to evaluate the model's performance on unseen data (test data) to assess the ability of the model in generalization. Thereby we utilized the aggregated results from both training and testing to determine the most suitable model. For instance, in Figure 3, we can see that both LSTM and AR-LSTM models performed well on long-term predictions during the validation process, while their performance dropped considerably on the unseen data. In this study, we used

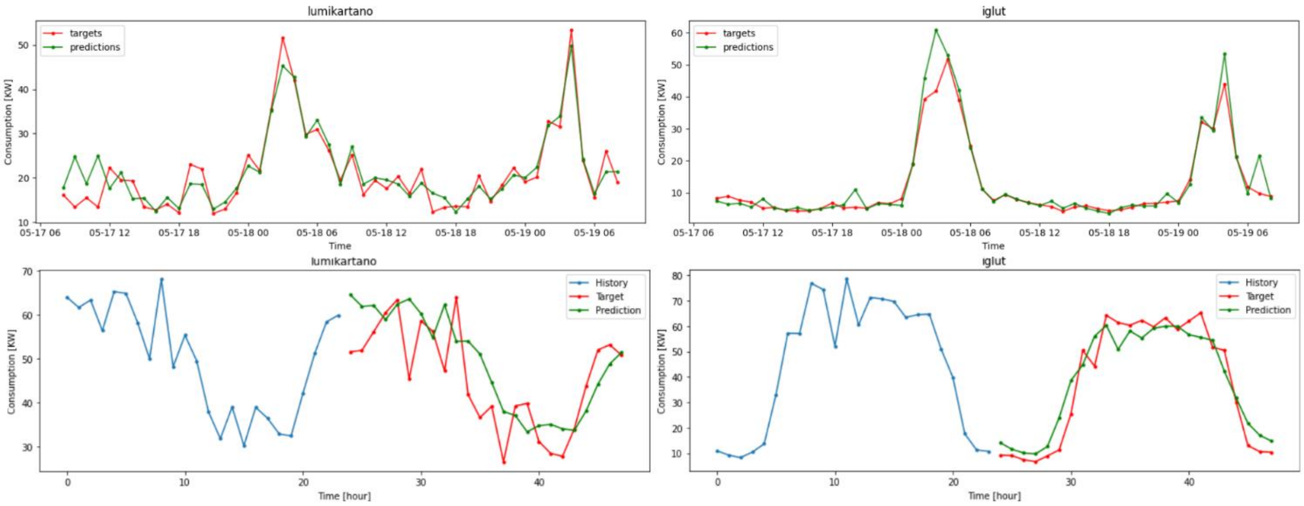

Figure 3 (top row) XGBoost model performance during the validation process. The line plots represent the performance of the model for the specified period. Here, the model used the consumption load information from previous hour to forecast the consumption load in the next hour. (bottom row) LSTM model performance during the validation process for long-term. The line plots represent the performance of the model for the specified period. Here, the model used the consumption load information from previous 24 hours to forecast the consumption load in the next 24 hours. The history is the information provided to the model to forecast the values in the future. The target values (red line) are the actual consumption loads while the prediction (green line) is the consumption load predicted by the model.

repeated k-fold cross-validation [11] to evaluate our models and improve the estimated performance further. Furthermore, the criteria for choosing a suitable model for long-term predictions are different from that of short-term. In both cases, it is clear that the model needs to learn and capture the underlying dynamics within the given dataset. For short-term prediction tasks, we looked for the model which obtained the lowest error during both the validation and test processes. Yet, in addition to that, for long-term prediction tasks, we look for models that could capture the peak values closely. Indeed, the long-term prediction tasks involve higher complexity, as the predictive models are required to capture and extract the long-term time dependencies. Therefore, preserving a model which can carry out long-term predictions with a reasonable low error would suffice the need. Note that this error rate depends on the task and might vary from case to case.

For a deeper future forecast to support mobilization, the LSTM model came out on top. A comparison between the best candidates for long-term predictions is shown in Figure 2. Based on the observations, the densely connected model could capture the patterns within the time series with relatively good accuracy. Nevertheless, the model's predictions for peak loads were not as precise as the LSTM model. Like the densely connected model, the CNN model could follow the consumption load patterns within the time series. However, the CNN model achieved significantly lower performance than the other models. It is worth noting that when we looked deeper into the densely connected model performance, we discovered a degree of randomness entangled with the model's predictions. Indeed, it appeared that the model learned the mid-range values rather than the peak consumption loads. Besides, the AR-LSTM model performed closely to the LSTM model in terms of accuracy and loss. However, when we inspected the actual model's predictions, it depicted a similar behavior as the densely connected network. Therefore, we decided to use the LSTM model for further work and forecast consumption loads. Figure 3 presents the performance of the LSTM model for long-term consumption loads prediction.

Table 3 Distribution of consumption values of Lumikartano and Iglut sites.

Site	count	mean	std	min	max
Lumikartano	21973	-2.897	1.0	-1.209	3.660
Iglut	21973	9.500	1.0	-0.980	4.393

We can see that the performance of the XGBoost model show lower accuracy for the Iglut site compared to Lumikartano (see Table 2). One reason could be the added uncertainty related to the influx of solar power in this part of the distribution grid. For the long-term prognostication (See Table 3) the accuracy varied too. The 24 hour outlook can be viewed both in terms of hourly changes and long term trends. From Figure 3 the trend established by the long-term prediction is fairly obvious and informative, while in some instances the next 24 hour prediction looks poor with up to 30% mismatch from the ground truth. A case in point is a situation where the predictor overestimates a peak of 70 kWh/h, while the true value is 53kWh/h. Another situation shows a brief underestimation of 14 kWh/h against the true 55kWh. The former is a 25% overestimation and the second is a brief 75% underestimation. However, the underestimation is in regions with lower loads, which we are not so concerned with. The correct trend is soon picked up too. The overestimation typically happens when significant peaks are foreseen. If the vehicles are able to discharge in a V2G situation with a power rate between 3 or 6 kW, the early notification based on the overshooting prediction would imply a 24 hour mobilization of up to 24 vehicles in Set A, while the true value would imply approximately 18. But

with constant multi-step predictions of lesser horizons more accurate figures would lead to convergence towards a more accurate prediction and lead to an early dismissal of the surplus 6. Alternatively they could be included in the Set R to cover for the reserve in a rolling activation plan.
Consequently, the XGBoost and LSTM methods were adopted for further work for short-term and long-term predictions, respectively.

CONCLUSIVE DISCUSSION

Introduction of a V2G regime based on LEVs such as snowmobiles require good planning and for that good foresight. Both are essential in order to design a good management and control system for persistent reliance on the reserve power that such vehicles offer. The completion of such a design is still in the making in the project. What the research presented here proves, however, is that it is possible to make quite good short term predictions and satisfactory long term predictions. We could have possibly enhanced the multi-step prediction by introducing postprocessing by means of a moving average model. This would probably make the longer trend more salient. However, so far this element has not been included. What the reported work emphasizes, that none of the models tested were absolutely suited, though the final result produced by the LSTM can be applied for practical purposes. The tolerance is catered for through mobilized reserves constituting the M set. Yet, there is room for improvement in the present multi-step approach. But as can be witnessed, linking ongoing prediction to different future states for a V2G operation helps to control the process towards activation (Set A), where a fleet of vehicles discharge power at the same time to create and aggregated impact. Moreover it helps to provide an early notification for those that need to be involved (Set M). Expectation management is important if vehicles are in regular use. With sufficient lead time owners of vehicles can organize their day and week accordingly. As a part of the V2G management system, notification that specifies when the grid is open for recharging is also possible. This feature will be incorporated in the final management system. As can be observed, the low-impact periods in the grids in Finland are predicted too (see Figure 3). This means that the same approach can provide the members of the V2G regime with the necessary advance notice when it is possible to recharge, which in turn could facilitate personal planning. One issue posted at the outset of the project is whether for LEV owners with low battery capacity can be useful for V2G services. The answer has been provided during the work done, and the issue well resolved. LEVs are useful for V2G services despite the low battery capacity. In the case of the Finnish sites a peak curtailment of 20kWh/h would demand the activation of 4-7 snowmobiles (Set A) for 1 hour and additional 8-14 vehicles (in Set R) for 3 hours. To mobilize this number of units should be absolutely feasible here and in other communities of the same size. We think that the scalability potential is there and the same concept can be applied for similar purposes in areas such as Longyearbyen. Even if we look beyond the Arctic the same kind of concepts could be deployed for remote communities located in rural areas where the electric scooter or ATV is the main means of local transport.

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