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Forecasting Battery SoC for Electric Buses with Dynamic Route Information and Neural Networks

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Executive Summary

This work explores the suitability of a battery SoC forecast model based on static and dynamic road data, as a first step for a proof of concept of highly adaptive PTC. A Long-Short Term Memory (LSTM) neural network model was trained using a synthetic dataset generated by means of a backward-facing drive-cycle simulator and route data with relevant conditions for the operation of a bus.

The obtained model performed predictions with less than 6.5% RMSE, even under disruptive system events. This demonstrates an interesting potential for applying Machine Learning and Highly Adaptive Powertrain Control integration to aid bus systems optimization by using realistic operation conditions instead of worst-case scenarios, which usually leads to over-dimensioning, and indirectly, to an increased cost of ownership of the system.

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1 Background

The need for reducing the fleet Total Cost of Ownership (TCO), from the operators' point of view, plays a central role for the adoption of alternative powertrain technologies in bus fleets. Initial system costs are known to be higher for electric bus fleets, not only because of the elevated entry cost of the vehicle technology, but to accounting for the charging infrastructure that is required as part of the initial investment. Most of the times, it remains in doubt whether adopting such systems can have a comparable TCO to the current fleets (mostly diesel-based) or will represent either higher costs or savings over its entire lifespan.

While PTOs and vehicle manufacturers are already looking at the challenges with a more comprehensive approach, the possibilities offered by the integration of connected vehicles and smart infrastructure expose the need to add extra layers of optimization.

Considering exogenous conditions and dynamic route information on the fly -or in simulations- to manage the energy consumption more accurately, could be achieved by using short-term forecasts of passenger counts, traffic flows, ambient temperature or energy costs (for charge scheduling). This would allow to use smaller batteries while compensating the inherent risks with robust and more active energy management.

Advanced battery management and range forecasting will be a core functionality for connected vehicles, but although sensible research has been done in this field during the last decade, it is oriented mostly toward freight applications and personal vehicles, a prior literature review showed no specific application developed for public bus systems.

We think that predictive route energy planning could help to assist the system co-design and infrastructure planning for fleets of Battery-Electric Buses, as well as its operation where more mature developments are already in the market (mainly for hybrid private vehicles). This motivation is partly pushed by the availability of live road data.

The proposed machine learning approach will be centred in the use of a NN to forecast the battery SoC of an operating bus. This suggests several possible applications, from assuring that the vehicle will reach the next opportunity charging, estimating the SoC at the arrival to the charging point so the charging operation can be scheduled when electricity can be purchased at a lower price, identifying or predicting system faults, etc.

1.1 The Study Case, Eindhoven’s Airport Route 401

Until early 2018 Eindhoven had the largest BE-Bus fleet in Europe, recently surpassed by Amsterdam´s newly deployed fleet of 100 new 18m VDL Citea BE-Buses Figure 1. Eindhoven´s fleet accounts for 43 18-meter BRT articulated vehicles that provide service to multiple lines of the system along with conventional vehicles [1].

The Dutch manufacturer VDL has a strong presence on the bus and coach market across Europe, and it has positioned itself as a leader across the sector in various countries. This has allowed them to win important contracts with the main PTOs in recent years.

Figure 1: VDL Citea buses at Eindhoven’s airport, lines 400 & 401.

Due to the region’s relevance to the electromobility and Sustainable Transport sectors, Eindhoven is an attractive location that is known to be an open testing ground for new technologies. With strong presence of the high-tech sector, the city has taken the lead in experimentation of new mobility-oriented services and Smart Cities, making extensive use of the connected infrastructure that is available in the city [2].

The operator of the route is Hermes, they provide a good online ticketing system with direct access to live information about routes and stops, therefore, most of the buses are already equipped with GPS tracking, Information that is shown in the website map as seen in Figure 2. The information is displayed along with the scheduled arrival time of the corresponding bus to each stop (as per the time-tables). Additionally, the system displays the actual time differences of that trip for each of the bus stops already covered [3]. That means, the historical information about the trips is available at some point and it could be downloaded and stored for future use. It is unknown if the GPS logs is stored by the operator for future use or not.

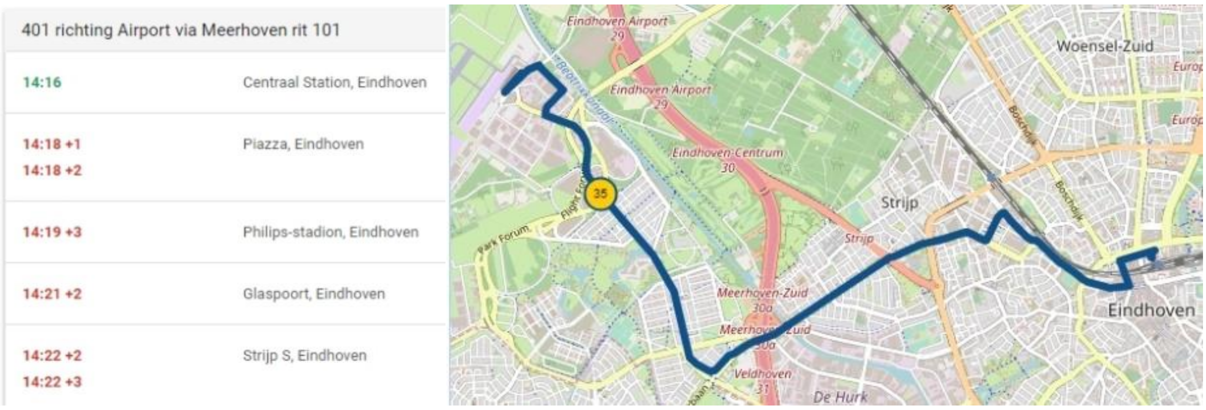

Figure 2: Live GPS data from Eindhoven line 401, bus location and trip number indicated.

1.2 Charging Infrastructure

For those not entirely familiar with electromobility, here are some very basic but useful remarks about why the charging system must be included in the design of the buses and vice-versa.

Chargers are provided in different power levels, ranging from ~30 Kw (overnight) to ~300 Kw (Ultra-fast charging). Batteries with different characteristics must match the design requirements the charger. So far, depot charging is the preferred option, for PTOs [4] since it offers an operation and scheduling system very similar to the current fleets with minimal adjustments. This because operators seek to get vehicles that are straight replacements [4].

But that means that the ranges (mostly dictated by battery capacity) of these vehicles need to match that of the diesel buses they are replacing, but that can become very expensive for BE-Buses. While ultra-fast charging provides some advantages, smaller and lighter batteries, and therefore more affordable buses (at the cost of increased infrastructure investment), but one of the downsides, is the battery degradation. Charging at higher energy levels means that the degradation of the components is faster too. Making necessary to protect the batteries from reaching its end of life prematurely. In any case, highly adaptive predictive powertrain control combined live road data could lead to more precise dimensioning of the system regardless of the which is the most suitable solution for a certain city -if that means only one solution being sufficient-.

2 Methods and Approach

It is worth mentioning that the main intention of this work is to provide an exploratory work on the suitability of integrating "live" data and realistic operating conditions in the dimensioning of bus systems, rather than finding the best performing machine learning algorithm to do so, or determining the most influential variable on energy consumption, although this remains open for further work.

Previously recorded driving logs containing speed profiles of trips along the line 401 (courtesy of TNO Powertrains) were transformed and later combined with static and dynamic route information, and fed to a drive-cycle simulator which generated synthetic datasets with the SoC information.

The dataset containing the SoC information then would be introduced in a neural network (LSTM type) to generate a prediction model.

The variables selected to build the model were based on [5], so the influence of the selected variables to the energy consumption of the vehicles has been studied previously [6] and used as reference for this work. Nevertheless, recent work [7] shows an extensive sensibility analysis of the influence of various noise factors across different powertrain topologies, finding that for most powertrains, the second most influencing variable is the driver behaviour (aggressiveness).

To be able to integrate this into the model, is necessary a different dataset with driver pedal inputs which was not part of the initial research that collected the sampled drive-cycles. Yielding impossible to include such factor in the training of the model.

It is also important to note that if we consider an optimal -yet unlikely- scenario where the drivers are very well trained and excel at driving in economy mode, the results could be very different. For the sake of this work we will consider that. Which leaves us with a scenario like the one here presented.

The HVAC heating and cooling requirements are regulated by standard for the driver, and passengers [8]. Ambient temperature can influence the energy consumption up to 60% additional energy in winter time and around 30% in summer time [9]. According to this reference, the temperature can be considered as the most important factor to consider when predicting energy consumption of operating buses. In this case the temperature and activation of the HAVC / heating system was programmed directly in the simulator itself according to the supplier specifications of the cooling (36 KW@40 °C) / heating (47 KW@0 °C) system and a rule-based approach.

Instead of target temperature or delta temperature vs exterior, as systems work, we opted for a simple rule-based model, activating cooling if the ambient temperature is higher than 20 °C and heating if it drops below this temperature, both systems reaching the maximum power demand at the specified temperatures and the total accessories power demand increases from a threshold of 10KW as shown in Figure 3.

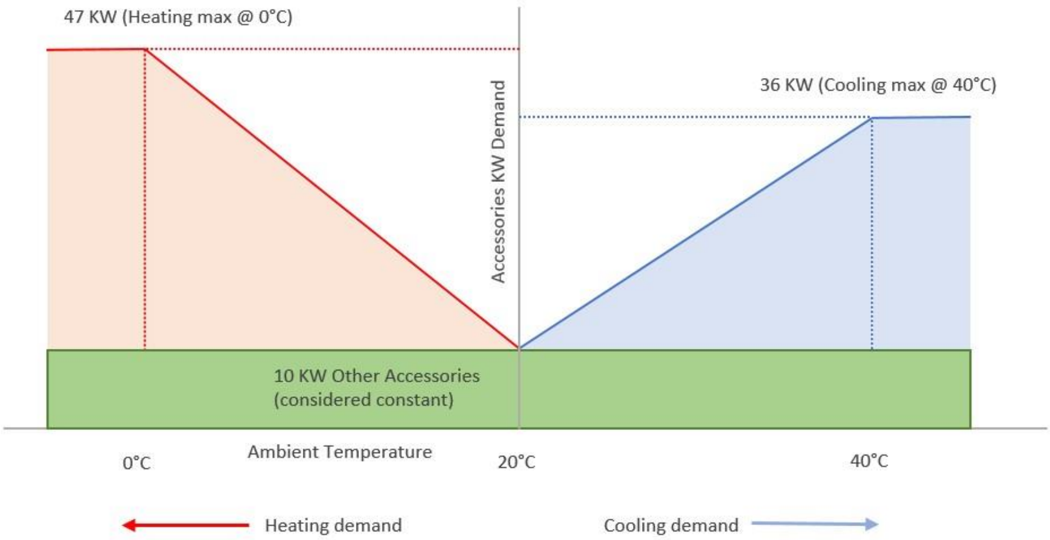

Figure 3 - HVAC Power demand, simplified model.

2.1 Drive-cycle Simulator

A basic power consumption model for an electric bus is briefly reviewed to provide a better understanding of the process carried by the powertrain simulator. More so, it will help to understand the importance of the variables on which the forecasting model relies. Although the operation of the simulator will not be discussed in detail in this paper.

As suggested by Vepsäläine et all, the model variables are classified in four groups, but re-grouped in two for easier identification, eBus System Variables (Control Factors, Tolerance Noise): corresponding to all inputs that might affect the model and are directly linked to the characteristics of the vehicle and later to include charging systems. This includes nominal values and deviations caused by degradation, maintenance etc. [6]

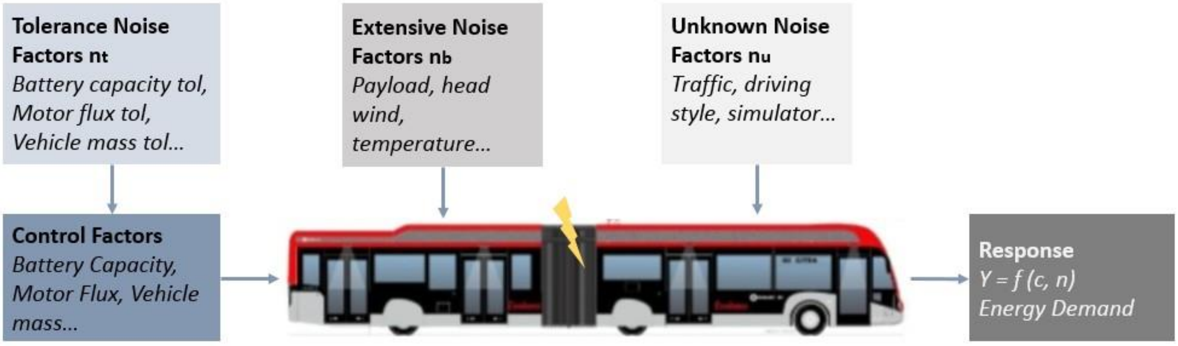

Figure1: Bus Model and Influencing Factors, adapted from [6]

Exogenous Predictors (Extensive Noise, Unknown noise): namely all other factors that have the potential to influence the energy demand of the operating vehicle. In this case is a mixture of historical, topographical and synthetic data. Other factors as road quality, driving behaviour and wind can be included one by one to increase the complexity of the system, at a computational cost.

The Simulator developed is based on FASTSim (The Future Automotive Systems Technology Simulator), an open-source program developed by The National Renewable Energy Laboratory part of the U.S. Department of Energy to evaluate different scenarios of automotive fleet electrification. For the purposes of this research, the Python version was used and modified according to the requirements of a BE-Bus, which is not included in the scenarios that the software currently handles. Neither the implementation of the HVAC control nor the variable payload (passenger counts) is part of the original software, thus it was implemented giving birth to BE-BusSim.

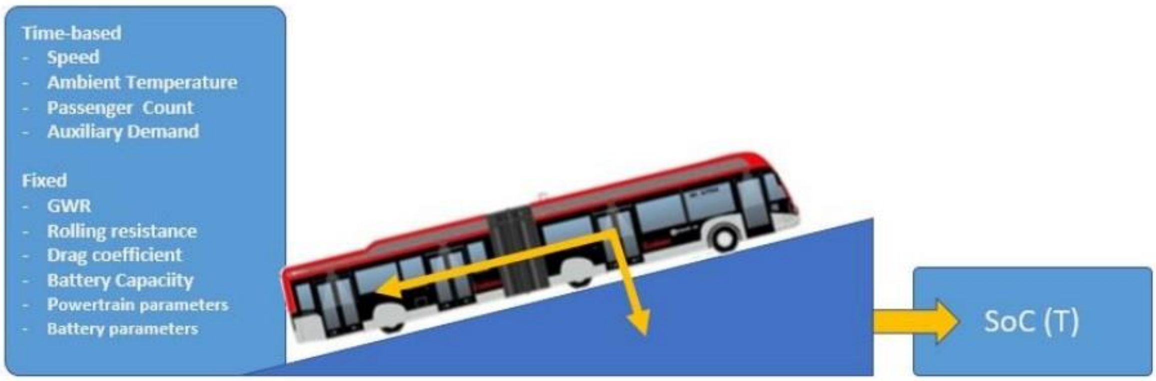

Figure 4 - Longitudinal Dynamic Model (BE-Bus), adapted from Towards ZEB transport, TNO

The program relies on a number of vehicle parameters (vehicle weight, min SoC to avoid premature ageing, electric motor power, regenerative braking output, frontal area, tyre radius, etc.) and route conditions (passenger count, road grade, ambient temperature, instant speed, etc). With this, and based on a Longitudinal Dynamic Model (LDM) of the bus, see Figure 4, it computes the energy consumption every second, allowing to compute t for as many points as the inputs were provided.

The result of the computations is a new dataset which includes the SoC in addition to the input variables, see Figure 5, and two extra outputs that are simply flags based on the SoC level. Warning flat is the SoC falls below 20% and an error flag which is triggered below 10% of SoC.

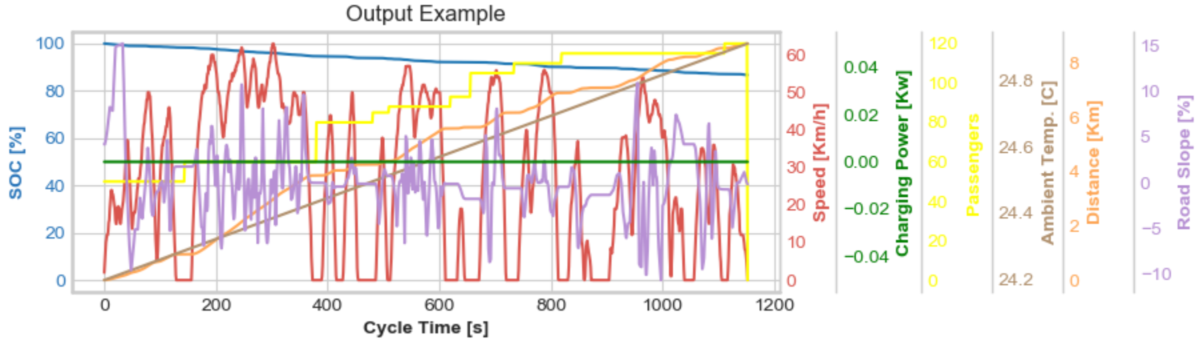

Figure 5 - Simulator Output vs Inputs, outbound journey displayed.

The Simulator performs correctly as long as the SoC does not go too low. It was programmed to keep the battery above 0% SoC so the simulation can be completed. However, this behaviour is not expect on reality, it is well fitted for research purposes. Ideally, the simulator can be updated to stop the operation when this happens. Below in Figure 6 we show the result of the dataset generated with one disruption. The black arrow indicates a missed opportunity charging (OpCharge).

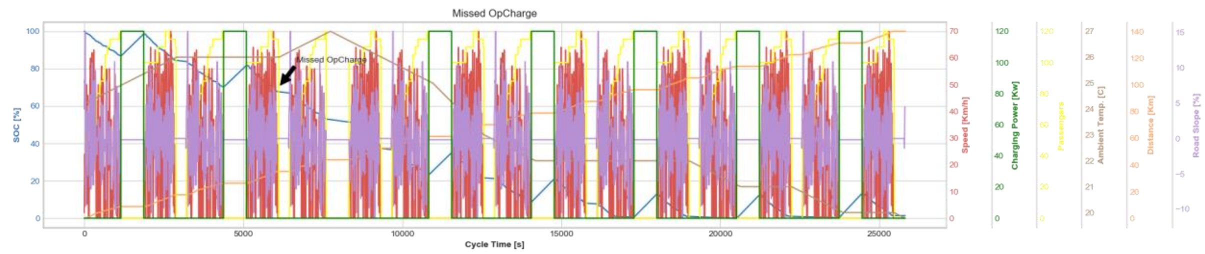

Figure 6 - Multi-journey simulation output (One missed OpCharge)

2.2 The Neural Network Model

One of the advantages of machine learning methods is that all the parametrized information is not necessary to produce similar results to those of a simulation that accounts for as much detail as necessary. Facilitating the generation of new models and speeding the analysis of different scenarios while providing only some inputs, in this case, the route information and the SoC will be enough.

The neural network will receive as inputs all the route information and as target the SoC, meaning that it will obtain the embedded information that relates all these variables yielding to a prediction model, which can be used to produce predictions of SoC for window of time in a similar fashion to those produced by the simulator but without all the required parametrization. Therefore, it would be applicable to any bus of any manufacturer, size, route, etc.

Input variables:

Battery SoC. Obtained from the results of the simulator, it is the target of the model.

Location. The model was transformed to a linear model, where everything occurs at a given position along the route. All the information is unfolded and every meter there will be an input for each of the variables.

Road grade. The information can either be gathered from GPS trackers or from the open data corresponding to the route being modelled. In our case the second option was used since the GPS information was not available. In this case, the speed profiles, the location of the bus stops and sharp turns were used to spatially align the datasets.

Trip leg. As the information of the route is entered only as a function of distance, each leg of the journey is further identified to distinguish outbound from return trips as a binary variable.

Ambient temperature. Two days were chosen to use in the simulation, both days have temperate climate, however one has average temperatures of 11 °C while the other is on the 20 °C. The temperature is the most important variable, and modelling the variable consumption of the HVAC consumption is directly linked to this information.

Passenger counts. This data was not gathered with the bus operator. While it might be available, it was not included in the dataset, nor it was provided by the company. The passenger counts, however tend to have an observable pattern. As this line has very busy start and end points, the central station and the airport, the passenger load tends to be half capacity at start of each trip and picking more passengers up to the middle of the route, then slightly declining toward the endpoints. For simplicity and lack of data, this observed pattern was used to build a pattern to be used as a proof of concept, but it can be easily updated later with real data or using statistically generated passenger load distributions.

There is also an interesting behaviour to note. Since planes do not land with the same frequency as the bus arrives to the airport, some buses are very full when departing the airport, while other trips are empty. This makes a good testing case to study for the forecasting model, since it means that the inputs change sufficiently, which contributes to decrease the bias of the model.

Charging points (Opportunity charging). Along with the bus stops information, the available charging power can be stated as a binary variable, containing either zero for the section of the road that does not correspond to the charging location. To simplify the model, the simulator was modified to provide a binary flag for the times when the bus was charging and for those when even standing at a charging point, it was not required. Charging was enabled if SoC was less than 80%, also.

SoC and Battery life (warning indicator, error indicator). As already explained, the first is just an indicator that the bus is entering in an operating condition where degradation of the battery life is greater than normal, while in the later, the error flag means that the vehicle has entered in a state where main systems are subjected to malfunction due to the battery not being able to supply the requested power at any given moment, at this point the bus would need to make an emergency stop for safety reasons, and therefore, the service would be interrupted. We aim to discover these occurrences so that designers of the system can use this information to dimension the system.

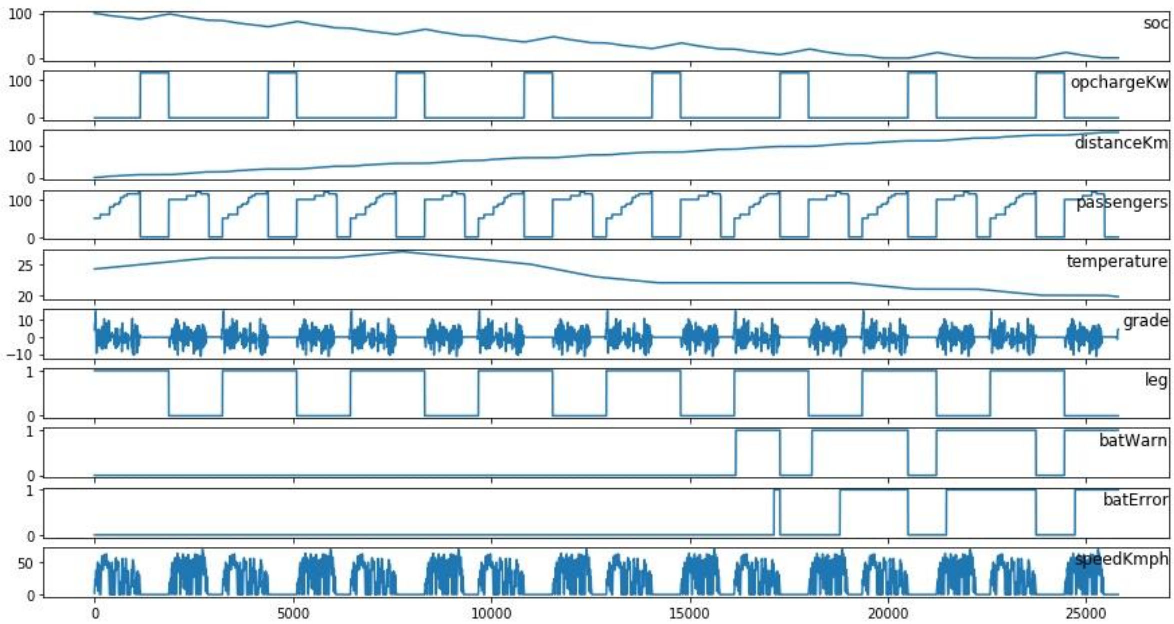

Figure 7 – Example of the neural network inputs dataset, 8 journeys, X axis is in meters.

Choice and Setup of the NN

For this study, it was defined that a simple Neural Network will be used, merely as a proof of concept to the control optimization approach. Tuning the network architecture or fine tuning of parameters will be left for further work.

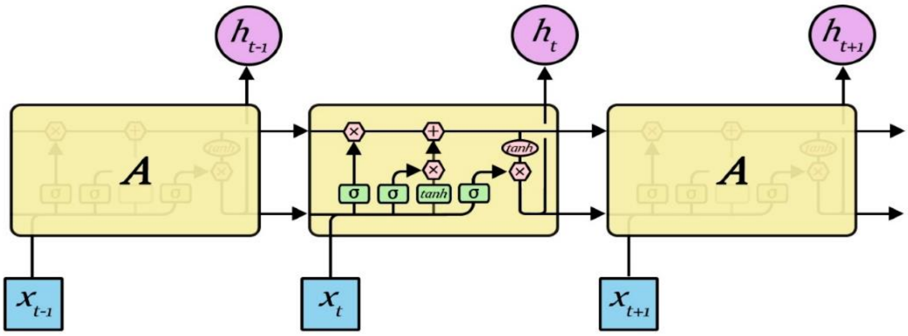

Figure 8 - LSTM Neural Network, Schematics.

An LSTM was chosen for this supervised learning task. In part because it allows to easily setup the forward and backward timesteps, but also because the algorithm is known to outperform most of the other methods in a good variety of problems. Knowing that recent studies have shown that new algorithms have been developed to take advantage of hardware acceleration and that have already shown superiority against the well positioned LSTMs. The Hierarchical Neural Attention Encoders not only offer advantages at both memory and hardware optimization levels by enabling parallelization, but also it requires less computational steps for learning, this will be explored in future work.

This certainly falls out of the scope of the present project; however, it is important to take note for future development. But the application of NNs coupled with control has been reviewed in [10]–[12][13].

Two network architectures were chosen based on an initial run with a dataset composed of ~25800 observations, which was split in train and test at half. (~12900).

The reason behind for this partitioning, half of the dataset, the one intended for development (validation dataset), shows a very different behaviour to the first half. This provides an excellent opportunity to test the network with data that resembles system faults. In this case, the dataset represents a very low SoC, -beyond the limits that the system would reach in normal operation-.

This condition was caused by the algorithm of the PT simulator. It is designed to provide "extra" energy to the battery to keep the simulation going until the task is completed, but this is far from reality. This could be easily found to be a fault in the system, therefore, of interest for evaluating the predictor performance.

Training the Model

Some trials were run prior to using the full dataset, to ensure that the processing time was acceptable, and to determine the number of epochs to avoid overfitting.

The following architecture was decided after evaluation of some basic setups offering the lowest RMSE with low training and prediction times. The prior iterations mainly searched through the number of units (8, 16, 32, 64, 96, 128) and the batch size (32, 64, 96, 128). This however is not reported.

Two multi-categorical LSTM networks were setup (with Keras library) with the same characteristics but different prediction time-steps to evaluate if multi-step offers a noticeable advantage:

Table 1 - LSTM Results (RSME)

LSTM 1, **single step**	**Timesteps**	1 lag steps (…t-1) and 1 fwd step (t+1).
	Input Neurones	32
	Output Neurones	1
	Batch Size	96
	Target variable	SoC
	Multi-categorical	Yes, 10 features.
LSTM 2, **multi-step** (backward)	Timesteps	4 lag steps (…t-4) and 1 fwd step (t+1).
	Input Neurones	32
	Output Neurones	1
	Batch Size	96
	Target variable	SoC
	Multi-categorical	Yes, 10 features.

Both models (single-step and multi-step) were trained initially for 50 and 30 epochs with different size configurations, showing in virtually all cases an optimal number of epochs around just below 20. The training was carried out for 17 and 18 epochs on both networks. Early stopping was performed manually, in this case. The results of the predictor will be covered in the next section.

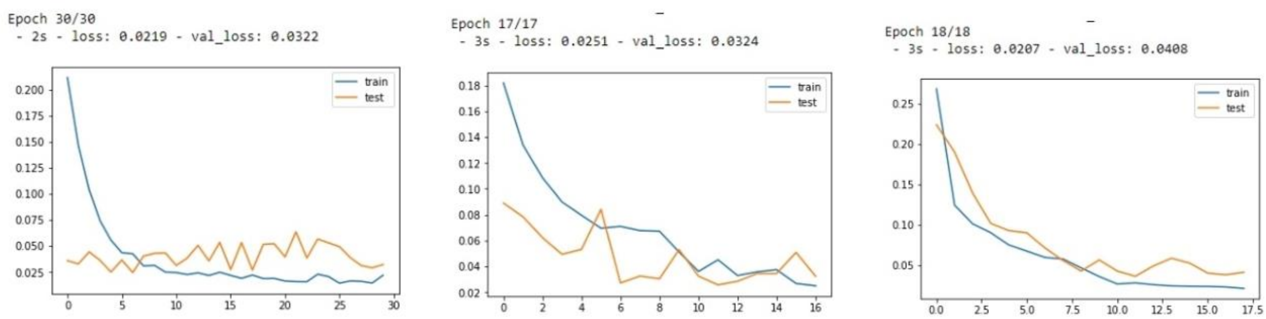

Figure 9 - Loss During NN Training

3 Results: Models and Performance Evaluation

For this model, we used three datasets, train, development and test. Whether the development part of the dataset is used in the training, the test datasets are completely independent, therefore are stressing the system for generalization and overfitting. Overall the model performed well, with a maximum RMSE of 6.24 and below. The model shows potential given the assumptions and lack of data.

Both models (single-step and multi-step) achieved a reasonable performance, given that the input data was limited to around 26K observations for time constraint reasons. Increasing the training dataset and could help to increase the performance of the model, but it remains to be tested. Assembling these datasets was labour-intensive, but the model can be applied to existing data already and provide some interesting information.

Although the temperature data, slopes from back and return trips, are different, the speed and passenger information remained the same (8 cycles). This might have some influence over the results obtained. Nevertheless, the models were tested on two additional datasets, completely different from the validation one.

Table 2 - LSTM Results (RSME)

Model	MRSE Validation: Low battery SoC	MRSE Test Dataset 1: Sudden Full Passenger Load	MRSE Test Dataset 2: Missed Recharging Opportunity
LSTM t-1 / t+1	4.966	1.3726428	6.428
LSTM t-4 / t+1	3.880	1.744	6.140

SoC Forecasting Subjected to System Disturbances.

Error values for conditions (disturbances) that were not present in the training dataset were expected to be higher, a-priori. The networks were purposely trained with data corresponding only to normal operation conditions, and it was one of the goals of this work to identify how well the models can learn to be capable to predict the SoC even under un-recognized conditions for any of the features.

As seen previously, the Models still have plenty of room for fine tuning and the forecast is already below 6.5% of RMSE. Also, the road data that was used comprises only a part of the provided dataset with recorded bus trips. The datasets included had around 10 full trips with varied speed profiles (along the same route - Lijn 401). The downside, as seen exposed previously is that the driving logs require intensive data transformation and manual pre-processing to be usable in the simulator.

The Figure 10 corresponds to the "test" executed on the development dataset shows on the vertical axis the SoC against the time in seconds of a series of bus trips. This corresponds to the development dataset, that is, the test part of the initial dataset that was used for both training and testing. It must be noted that for this work we have used train, development and test datasets. The test datasets are completely new to the network. The model was trained with the first half of this data, corresponding to SoC values from 100 to 40%. Testing the model with the remaining of the dataset and obtaining a prediction with 3.88 RMSE, see Figure 10.

Figure 10 - Low SoC Scenario, development dataset.

Disruptive event: Missed Opportunity Charging Scenario

The dataset was prepared to simulate a missed opportunity charging, this scenario could be a failure of the charging system, on the communications, a fault on the bus system, or a purposefully scheduled no-charge for balancing the bus network schedule due to some other disruption.

The model performed with a RMSE of 6.14, in this case, the model was trained with completely different data, which shows that the model is robust enough and generalises well.

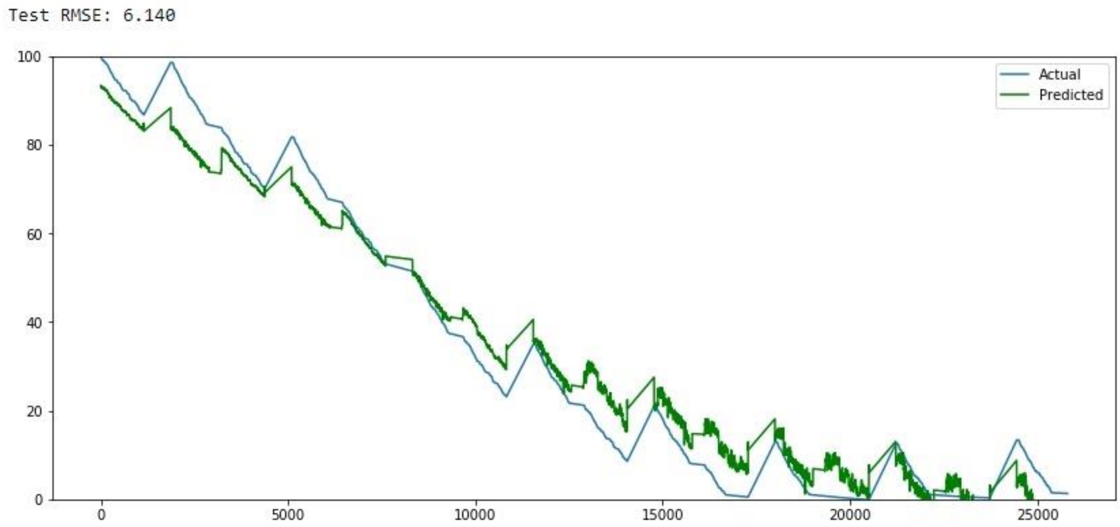

Figure 11 - Missed Charging Opportunity Scenario

Flags for Powertrain Control (Under Sudden Passenger Surge Scenario)

In Figure 12 the battery status flag outputs from the simulator are tested. It can be seen that the flags are triggered at the stablished thresholds of 20% (warning) and 10% (error). These flags could be use to trigger actions for a highl adaptive powertrain control within the simulations. Including scenarios of fault where the system can indeed continue operating, for example turning off the HVAC could be an option to running out of battery in a situation of unexpected congestion on the road.

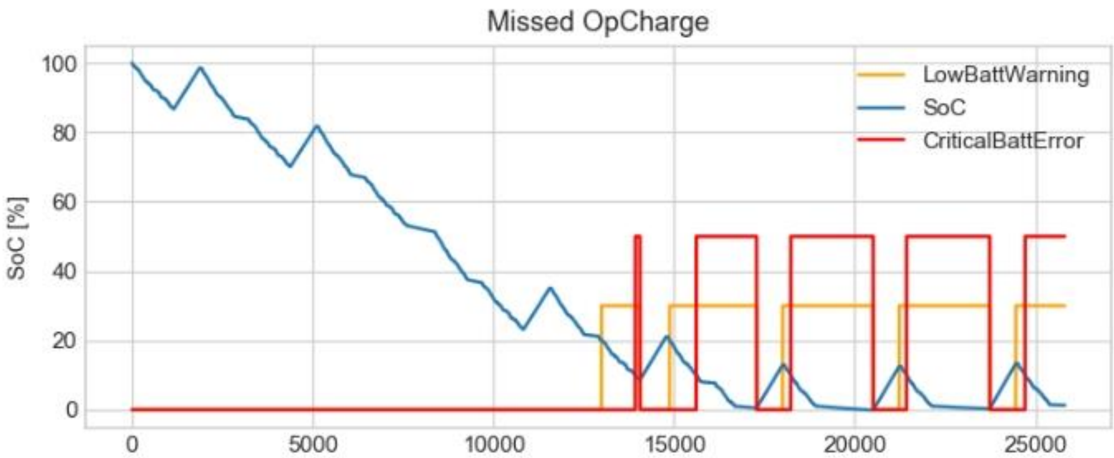

Figure 12 - Battery Status Flags, Multi-trip

The model was also tested with a known condition that occurs near the Philips Stadium in days when events are held in there. Soccer games, concerts, other mass events cause some level of disruption in the transport systems. In this case, it is known to have uncommon sudden load increase of passengers and road congestion. This simulation was made to account only for the full bus capacity. The result shows that the Predictor can adapt and forecast the SoC within small error see Figure 13.

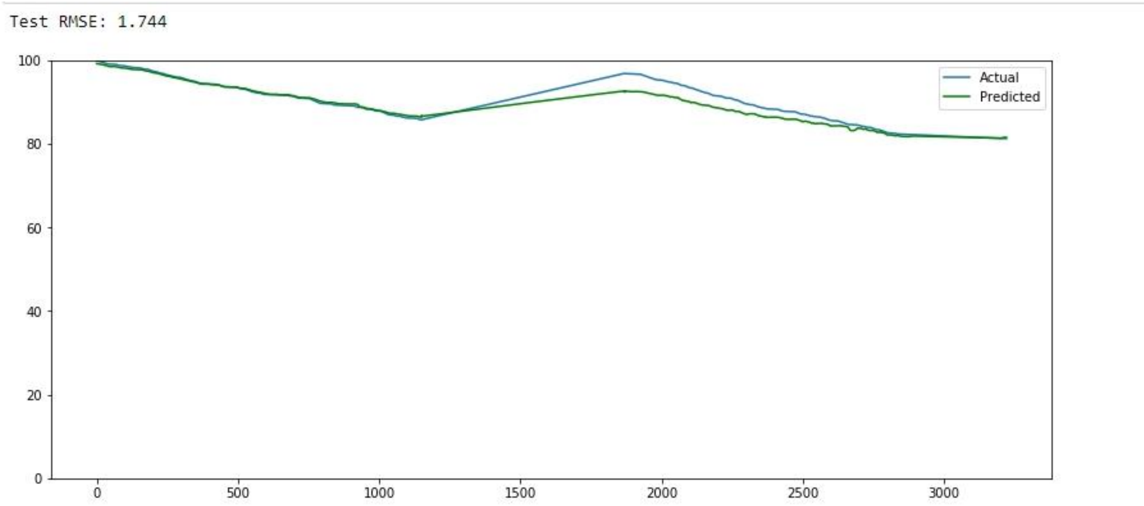

Figure 13 - Surge in Passenger Load Scenario, Single round trip.

4 Conclusions

The PTC plays a key role in the energy consumption of the vehicle. Considering a system co-design approach that incorporates the infrastructure, vehicle and control system would allow to fine tune and keep historical information of the most important operative parameters. This information could be updated live and fed to forecasting models like the one implemented here. This could be advantageous to plan and schedule charging times for example, based on the electricity costs.

In this case, advanced control offers the advantage not only of predicting the SoC under normal and disruptive conditions with an acceptable error (at least in this proof-of-concept). The relevance of this relies in allowing the designers to evaluate the system or individual component choices under different scenarios based on realistic operating conditions. Making possible to also quantify the risks (i.e. not reaching the next charging point) for the different configurations, and the powertrain strategies that could be implemented under such cases to extend the range in case that a forecast determines a risk situation.

4.1 Future Work

Moreover, these trained models could be implemented as Advanced Powertrain Control Strategies in live time to improve energy consumption and cut operating costs. This along with a more detailed Bus Control Model presented and similar tools, have the potential to increase the interest of bus operators and authorities to upgrade their fleets in a shorter future.This could also be applied to already operational systems, as a feedback loop to the driver, externally to the PTC. Allowing the driver to take decision of how to save energy, either by implementing eco-driving, switching the HVAC off opening one door instead of three. Applications to modify the driving behaviour could take a huge advantage of this type of technologies.

This model could be modified to predict a “reach or no reach”, a binary output to know if the bus will make it or not to the next charging opportunity. Generating this under realistic conditions could help to decrease the size of components like the battery without compromising the robustness of the system, that is, offering the same service level of the component dimensioned based on worst case scenarios.

5 Acknowledgments

We would like to thank to the TNO Powertrains department for the data provided for this work.

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