

Eco-Driving System for Energy Efficient Driving of an Electric Bus

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ABSTRACT

This paper presents the design of an Eco-Driving Assistant System (EDAS) in which the main goal is to minimize the energy use of battery electric vehicles, in particular, vehicles utilized for public transportation. The system optimizes the speed profile of a real route schedule while satisfying the constraints imposed on speed and time. It includes a driver feedback and a driver scoring GUI which allows the driver improving his/her driving skills and comparing him/herself to a "theoretical perfect driver".

The system also includes a backward simulator that generates information related to the vehicle operation under the particular route to be optimized. The output information from the simulator is used as an input to the optimization algorithm. The simulator was validated using real data from a battery electric vehicle. The EDAS system was tested for three different driving profiles and energy consumption reductions of up to 30.33% were achieved.

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INTRODUCTION

Environmental concerns and rising fuel prices are two factors promoting the development of strategies and technologies to reduce the vehicles fuel consumption and emissions. Such goal can be approached by different means. While an extensive list of published work attempts to address the problem by optimizing the vehicle powertrain operation, more recently, a concept known as eco-driving is also being studied. It allows further contributing with the fuel consumption and emissions reduction by involving the driver in the optimization process.

For the particular case of electric vehicles, the driving range and performance are very sensitive to driving style. Thus, an eco-driving assistant system (EDAS) may be useful as a training tool for the driver, helping achieving the goal of maximizing the vehicle range. This objective is particularly relevant for fleet operators, which can benefit from these systems by lowering their operational cost. They can also use it as a tool to implement driver incentives for their drivers, encouraging them to achieve more efficient driving styles. EDAS can particularly be useful for city transit buses which are usually driven for more than eight hours a day on a predefined route. This route usually follows a stop-and-go pattern, traveling a significant amount of miles and using a substantial amount of fuel.

Most of the current eco-driving approaches focus on the optimization of the driving profile for conventional vehicles [1], [2], [3], [4], [5], [6], [7]. However, some authors are also focusing on hybrid and electric vehicles [8], [9], [10], [11].

In [1] the speed profile optimization is based on fuel consumption and travel time and considers the road slope profile. A suboptimal solution is proposed by using a set of action rules based on results obtained from applying Dynamic Programming (DP). In this approach, if the driver deviates from the original optimal velocity profile, the optimal speed is re-estimated. The research reported improvements of up to 8%.

The optimization in [2] is based on a piecewise linear function which defines the vehicle's fuel consumption as a function of engine speed and torque. The reported improvements go up to 20%. The approach in [3] assumes that traffic information, road grade and vehicle route are available through a remote cloud-computing system. Thus, the driving profile optimization is performed along the route, according to the real-time information and vehicle position. The problem is solved by using pseudo-DP and results of up to 14.02% improvement are reported.

Traffic lights timing and a feed-forward traffic estimator are used in [4, 5] respectively. The first attempts to generate a velocity profile that reduces the time spent in idling condition at stops lights, while the second estimates the evolution of the traffic on the route and uses it as a constraint in the optimization problem. These works reported improvements of up to 47% and 21%. The approach proposed in [6] employs a recognition algorithm to identify traffic signals which force the vehicle to a stop and derives the optimal deceleration pattern to stop it without using the brakes.

Malikopoulos et.al. [7] propose an optimization framework for conventional vehicles, which uses a set of polynomial meta-models to represent the fuel economy. In this research, the instantaneous fuel

consumption is estimated as a function of the speed and acceleration and is minimized to find an optimal velocity profile. This approach yields up to 15.9% improvement in fuel consumption.

In [8], the speed optimization for hybrid electric vehicles (HEV) includes the battery state of charge as a part of the cost function for the optimization problem. This approach is evaluated for the case of a power split configuration and results in a 10% improvement in fuel use.

The optimization described in [9] focuses in the velocity optimization for hybrid electric trucks. It assumes that information about the speed limits, curvature and road grade is available and uses it to solve the optimization problem. It also accounts for the vehicle mass changes. Finally, [10] and [11] focus on the velocity profile optimization for electric vehicles. They solve the optimization problem by applying Pontryagin's minimum principle and Particle Swarm Optimization algorithm (PSO).

This paper presents an EDAS designed for public transportation drivers, in particular, those who drive electric buses. The work described in this paper is built upon the algorithm proposed by Malikopoulos et. al in [7], adapting it for its use in an electric bus. The system optimizes a particular driving profile corresponding to a real bus route to minimize the electric bus energy consumption while satisfying the involved constraints. The proposed system includes an online driver feedback and an offline scoring module that can be used by the fleet manager to compare drivers against a theoretical “perfect driver”. In this case, in addition to energy consumption, the bus predefined route schedule becomes an additional optimization objective.

For the implementation of this system a backward simulator of an electric bus was created to generate the data related to the electric bus operation for the particular route to be optimized. The simulation data is used as the input to an optimization algorithm to generate an energy optimal velocity profile. The optimized velocity profile and the predefined route schedule are used to give real-time visual feedback to the driver while driving the route. Finally, the real driving profile is compared off-line to the theoretical optimal in order to assign a driver score based on the fuel efficiency and the route time schedule.

The remainder of this paper is organized as follows: [section 1](#) presents an overview of the system. [Sections 2, 3](#) and [4](#) describe in detail the electric bus simulator, optimization module and proposed feedback and scoring unit. Finally, The results are presented in [section 5](#) and the main conclusions and future work are discussed in [section 6](#).

SYSTEM OVERVIEW

The proposed EDAS prototype is mainly focused on public transportation companies, which want to improve their drivers efficiency and reduce the vehicles operational cost.

As illustrated in [Figure 1](#), the system consists of: (a) an electric bus simulator, which generates information related to the performance of the bus when driving a particular route schedule; (b) an optimization module, which provides the optimal driving profile that minimizes the energy consumption for a particular route; and (c) a feedback and

scoring unit, which presents the relevant information to the driver in real time and rates a driver by comparing his/her performance with the results from the optimization module.

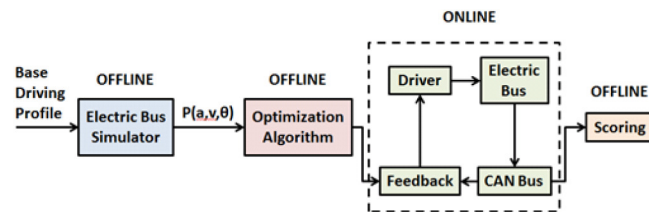


Figure 1. Proposed Eco-driving system structure.

Once the driving schedule has been defined, a base driving cycle is used as input to the electric bus simulator, which generates information about the acceleration, instantaneous power and total energy used by the electric bus. This data is fed into the optimization module to generate the optimal driving profile which minimizes the energy consumption for that route. These two processes are executed off-line, that is, prior to the start of the scheduled electric bus route.

The optimized driving profile is loaded into the electric bus prior to its departure. When the vehicle is on route, the real driving profile (the one that the bus driver is generating) is compared at each time step with the optimal one. At the same time, other parameters such as acceleration and instantaneous power are monitored and compared with the optimal ones. In this way, the feedback module can provide indications to the driver in order to improve his driving style, while meeting the route schedule requirements.

At the end of the route, the logged data is compared to the optimal one and a driver score is assigned to the driver. In the following sections, each module of the system is explained in detail.

ELECTRIC BUS BACKWARD SIMULATOR

To determine a vehicle's fuel/energy economy, simulations are performed over predefined driving profiles. Thus, an electric bus simulator is developed following a backward model approach. In the backward approach, the reference speed (driving profile) is applied directly as an input to the model. Based on this input, the road load, grade profiles and vehicle parameters, the requested tractive force is calculated along with the torque applied by the traction machine. This information allows computing the fuel/energy consumption and the operating conditions of the traction motor. The parameters utilized for the vehicle modeling are listed in [Table 1](#).

Table 1. Vehicle Parameters

Parameter	Value
Vehicle mass [Kg]	12759
Vehicle frontal area [m ²]	7.1
Electric Motor Continuous Power Output [kW]	100
Electric Motor Max Torque Output [N.m]	650
Battery Rated Voltage [V]	400
Battery Capacity [A.h]	200

Figure 2 illustrates the two main blocks for the vehicle simulator: a vehicle dynamics block and a powertrain block.

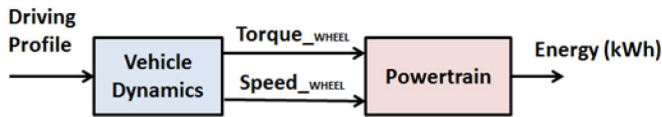


Figure 2. Vehicle Model.

Vehicle Dynamics

This subsystem, represented in Figure 3, uses the reference vehicle longitudinal speed v as input and calculates the resistive forces to determine the tractive force F_{trac} according to the vehicle longitudinal dynamics

$$m\dot{v} = F_{trac} - \frac{1}{2}\rho_{air}C_dA_f v^2 - mg\sin(\alpha) - mgC_r\cos(\alpha) \quad (1)$$

where ρ_{air} is the air density, C_d is the drag coefficient, A_f is the vehicle frontal area, m is the vehicle mass, g is the acceleration due to gravity, α is the road grade and C_r is the rolling resistance coefficient.

The dynamic axle weight transfer is used to calculate the available traction at each axle.

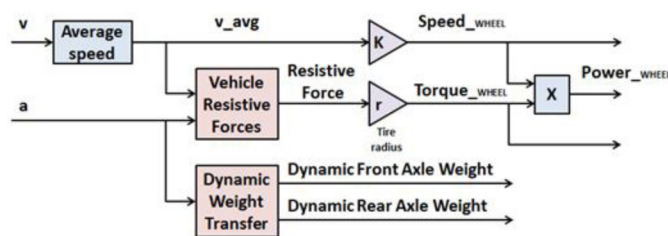


Figure 3. Vehicle dynamics block

The calculated values allow finding the corresponding outputs of the block: the wheel speed and torque.

Powertrain Model

The powertrain block diagram of Figure 4 contains the model of the brakes, transmission, electric machine, gear box controller and battery of the vehicle. Given the backward structure of the model, the information flows backward from the wheels to the electric machine and battery. The powertrain block takes as inputs the wheel speed and torque and provides the instantaneous power at the battery as its output.

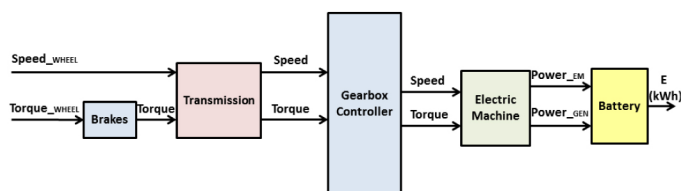


Figure 4. Powertrain block

Brakes Model

The front and rear braking torques T_b are calculated from the frictional rolling force C_r and the tire radius r , according to the following

$$T_b = \beta mg C_r r \quad (2)$$

where, β is the brake pedal position, m is the vehicle mass, and g is the acceleration due to gravity.

Since the vehicle has rear wheel drive, the rear braking torque is added to the wheel torque to get the effective rear braking torque. Finally, the total braking torque is computed by adding the rear and front braking torques. The maximum allowed axle torque is a function of the maximum axle weight.

The brake pedal position is calculated as

$$\beta = \begin{cases} 0 & \text{if } T_w \geq 0 \\ \frac{T_w + |T^*|}{-MgC_r r + T_{GE,MAX} + |T^*|} & \text{if } T_w < 0 \end{cases} \quad (3)$$

where, T_w is the wheel torque, T^* is the additional torque related to mechanical braking, and $T_{GE,MAX}$ is the maximum electric generator torque.

The brakes block takes as input the wheel torque and provides the torque for the transmission block as output.

Transmission Model

The transmission block selects the gear and the output transmission speed and torque in an optimal way. As there are two possible transmission gears and the simulator works backwards, two transmissions blocks are used. Each block assumes one out of the two possible gears as the current gear. Then, considering the gear box and differential ratios, and the gear box efficiency, the corresponding output transmission torque is calculated. This transmission torque is used as an input to the gear box controller which finally decides what the current gear should be.

This model takes as input the output torque from the brakes block and outputs the transmission speed and torque.

Electric Machine Model

This model converts the transmission speed and torque into electric motor speed, torque and power. The efficiency of the electric machine is a function of the torque and speed and it is determined from the efficiency map provided by the electric machine manufacturer. This model includes the generator and calculates the respective power going in or out of the battery.

Battery Model

The battery model is based on Lithium Titanate. It has been modeled as a static electric circuit as represented in Figure 5. The main parameters depend on the state of charge and SOC the temperature T .

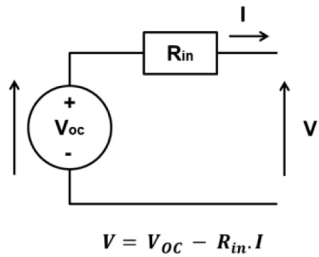


Figure 5. Battery electric circuit model.

The electrical model considers an ideal voltage source V_{oc} connected in series with the battery internal resistance R_{int} . Thus, the power request to the battery P_{batt} comes from the electric machine and is used to calculate the battery current as:

$$I = \frac{V_{oc} - \sqrt{V_{oc}^2 - 4R_{int}P_{batt}}}{2R_{int}} \quad (4)$$

The SOC is estimated by integrating the current and comparing that value with the rated battery capacity Q_{batt} of the battery pack. The charge transferred in or out of the cell is obtained by accumulating the current drained over time as

$$SOC = SOC_0 - \frac{1}{Q_{batt}} \int Idt \quad (5)$$

Simulator Validation

To validate the simulator, experimental testing was conducted at the Project Green test track which is located at the South Carolina Technology and Aviation Center (SC-TAC) [12].

The electric bus was driven along the test track on a short ideal driving schedule with different stops to emulate the process of loading/unloading passengers on a particular route. This ideal driving schedule will be identified as the base normal driving profile or the original driving profile. As shown in Figure 6, it consists of 12 straight paths and 11 bus stops with duration 1 minute each. The vehicle energy performance variables from the CAN Bus were logged and utilized to validate the simulator.

Figure 7 shows a qualitative comparison of the experimental and simulated data for the electric machine speed and torque.

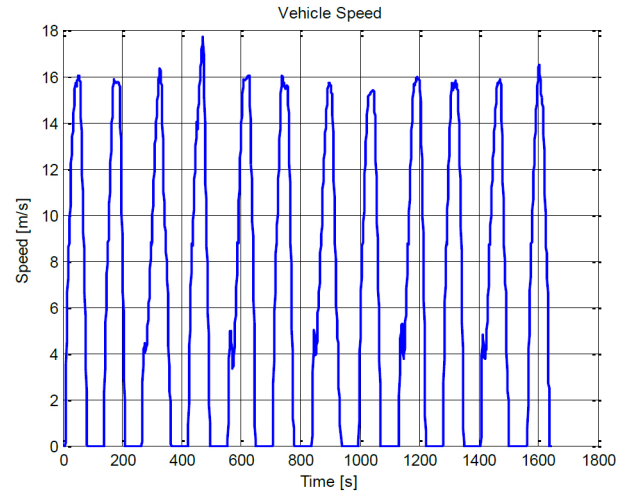


Figure 6. Base normal driving profile

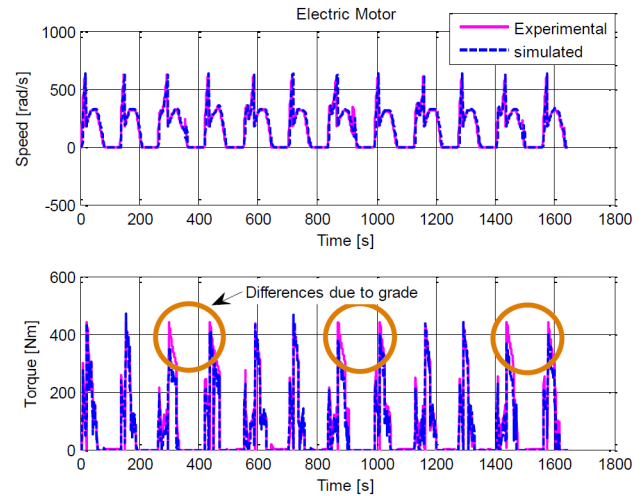


Figure 7. Electric motor speed and torque

For the case of the torque, some substantial differences are observed in the ranges of time 300 s to 320 s and 420 s to 470 s. They are the result of variations in the slope of the track, which could not be accurately measured to be used in the simulation. Hence, while the experimental data includes the load due to grade, the simulator neglects it.

The observed similarities in Figure 7 are supported by the scatter plots in Figure 8, showing correlation coefficients of 0.96 and 0.92 respectively. The outliers present in Figure 8 for the case of the torque are generated as a result of very fast dynamics that the simulator may not be able to capture or may delay to recognize.

Figure 9 shows that the simulated battery current, voltage and state of charge (SOC) data follows closely the experimental data. For the current case, the effect of neglecting the load due to grade, as mentioned for Figure 7, is observed too. The simulated SOC follows closely the experimental with an error of 3.96% in the final value. The square correlation coefficients for the battery current and SOC (Figure 10) are 0.917 and 0.912 respectively, which also support the validity of the simulator.