Energy Management of Electric Bicycles Given a Traveling Elevation Profile

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ABSTRACT

This research proposes a method for energy management in electric bicycles with Lithium-Ion batteries. This method optimizes the way energy is consumed to maximize the rider's comfort, subject to constraints on the battery State-of-Charge once destination is reached. The algorithm considers the elevation profile of the route chosen by the rider, predicting the battery energy consumption based on physical parameters of the user and the bicycle. The route is partitioned into equispaced segments, and the optimization problem is then formulated to decide when to pedal or when to use the bicycle electric motor. Binary Particle Swarm Optimization (BPSO) is used to solve the optimization problem, while particle-filter-based estimators are used to determine the initial battery State-of-Charge. We surmise that management of the variability associated with the State-of-Charge swing range, in a systematic manner, will help to increase the battery life.

1. INTRODUCTION

The use of new technologies or the optimization of the existing ones for the transformation of the actual energetic matrix becomes of great importance throughout the world in order to reduce the dependence of fossil fuels, by generating electricity with a low carbon index, increasing the efficiency and reducing the greenhouse effect gas emissions. The International Energy Agency (IEA) establishes that carbon dioxide emissions can be reduced in a significant manner by year 2050, if the transportation industry is modified with the incorporation of new energy sources (Agency, 2012).

In this regard, bicycles can play a crucial role since they are affordable, environmentally friendly, and in major urban areas perhaps the best choice to reach the destination due to traffic congestions (Corno, Berretta, Spagnol, and Savaresi, 2016), increasing the use of bicycles inside the cities on recent years, changing the perception of this vehicle. An example of this situation is that some companies encourage employees with benefits if they ride a bicycle to work. However, this solution might not be suitable for people that are not used to physical exercise, or if the traveling distances or the topography are an issue. Therefore the use of motorized bicycles can be a solution for this problem, and in particular electric bicycles (e-bikes) since they offer zero emissions when used.

This article proposes the development of an algorithm that considers the elevation profile of a route given by the user to determine on what segments of the route will the electric motor be turned on, optimizing the performance of the battery subject to the desired amount of energy that the user intends to have at the end of the route. This work did not consider vehicular traffic neither road signs. For this reason, energy recovery through the use of regenerative brakes is not part of the model. This article is organized as follow: Section 2 provides information about the e-bike. Section 3 explains the methodology used, and Section 4 shows the results obtained using the proposed optimization algorithm. Finally, Section 5 is used for the conclusions.

2. ELECTRIC BICYCLE

The basic principles of e-bikes establish that there should be a power flow controller that regulates the energy delivered from the battery into the motor. The electrical power generated by the motor acts simultaneously with the mechanic power produced by the user when pedaling transforming both powers into motion. The basic scheme is shown in Figure 1.

When riding an e-bike, the cyclist has three options (considering there is enough energy available): allow the motor to perform all the work, pedal at the same time the motor is working or, pedal without any motor assistance. Usually, e-bikes are powered by a brushless motor capable of reaching speeds between 20 and 25 km/h (Muetze & Tan, 2005). The full torque given by the transmission is a combination of mechanical power (generated by the user while pedaling) and electric power (generated by the motor). Typically, the e-bikes allow the user to determine the required torque level needed as support, and then the motor delivers that amount of power until the motor runs out of energy or when the torque level is changed. This approach might not be the optimal to manage the stored energy on the Energy Storage Device (ESD). To manage the available energy, it is planned to use control algorithms and sensors to monitor the metabolic state of the cyclist with the intention to save energy on those periods where the user is more active, and using the energy when the user gets tired, taking into consideration that there should be energy stored at the end of the route (Corno et al., 2016).

Managing the energy becomes relevant since depending on how the ESD is used, it influences the future performance of the battery and the way it delivers the energy to the motor, having a direct impact on the degradation process. The degradation process, reflected on the State-of-Health (SOH) of the ESD, is responsible for the way the energy is delivered and stored since the cycling capacity diminishes with the use.

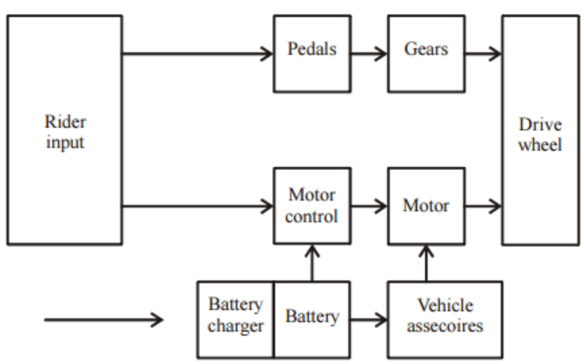

Figure 1. Basic scheme of an e-bike.

3. METHODOLOGY

Given an initial location and a destination for the route, the objective is to indicate in which zones the cyclist should pedal and assist the electric motor in order to reach the destination with the desired amount of energy remaining on the ESD. This way, there will be enough energy to return to the original location, or to continue somewhere else.

3.1. Route Partition

To define the sections where the motor will operate an optimization problem is presented. The motion of the e-bike can be characterized through the physics of the speed, and relating it to a function of the delivered power by the motor, hence creating an expression for the objective function. The optimization algorithm is considering the route as N finite segments determining in which segments the motor will be operating. In the following section the physical modelling along with the detailed parameters of the cyclist that define the kinematics and the dynamics of the whole system are explained.

3.2. Power-Speed Model

The physical model used to describe the kinematics of the cyclist considers resistive forces to the motion of the bicycle, relating the input power (delivered by the motor and the pedaling) to the actual output speed. The three main resistive forces are: gravity, friction and the aerodynamic drag.

The force of gravity affects the system as a function of the slope that the user faces. It could either accelerate or reduce the speed depending if going upwards or downwards. Equation (1) explains these phenomena, combining the gravitational constant g (9.8067 m/s^2), the total mass of the user and the bicycle in kilograms (W), and the inclination degree as a percentage where the user is (G).

$$F_{gravity}[N] = g \cdot \cos(arctan\, G/100) \cdot W \tag{1}$$

The friction resistance is the one that opposes the movement of the bicycle, and it is represented by a dimensionless parameter known as the rolling resistance coefficient (C_{rr}). It depends on the contact between the wheels and the road, the materials and the type if surface, as well as the weight of the system. It is described by Eq. (2).

$$F_{wheel}[N] = g \cdot \cos(arctan\, G/100) \cdot W \cdot C_{rr} \tag{2}$$

The aerodynamic drag is produced by the resistive force produced by the frontal air that pushes against the user and the bicycle. If the movement is faster the opposing air also increases. This type of force can be described as a dimnesionless coefficient (C_d) that captures the effect ot the air that goes through the cyclist depending on the clothes, and the type of air flow (laminar or turbulent). Equation (3) describes this type of force, whereas A represents the frontal area of the cyclist and the bicycle in (m^2), Rho represents the air density in (kg/m^3), and v is the speed at which the system is moving in (m/s).

$$F_{drag}[N] = 0.5 \cdot C_d \cdot A \cdot Rho \cdot v^2 \tag{3}$$

In this regard, the total force that acts on the system is given by Eq. (4).

$$F_{resist}[N] = F_{gravity} + F_{wheel} + F_{drag} \tag{4}$$

Thus, for every unit of distance that it is advanced it is necesssary to spend a certain amount of energy to recover from the resistive forces. Then the required work to be able to advance a distance $D(m)$ is given by Eq. (5).

$$W[J] = F_{resist} \cdot D \tag{5}$$

Considering that to cover a certain distance within a determined time interval, it is necessary to travel at a certain speed v, it is possible to calculate the required power that needs to be injected to the wheels, as shown by Eq. (6).

$$P_{wheel}[W] = F_{resist} \cdot v \tag{6}$$

The injected power consists of the combination of the generated power by the motor and the cyclist. However, there are some minor losses due to the mechanical components of the bicycle: chain, gears, etc. These losses are going to be estimated at 3% assuming that the bicycle is in good condition. This percentage is represented as $Loss_{dt}$. This way, the real power produced by the cyclist and motor can be related to the power of the spin of the wheel according to Eq. (7).

$$P_{wheel}[W] = \left(1 - (Loss_{dt}/100)\right) \cdot P_{motor+cyclist} \tag{7}$$

Finally, we can obtain the equation that relates the traveling speed with the injected power. This can be done with the prior equations and resulting into the new Eq. (8).

$$P_{motor+cyclist}[W] = \left(1 - (Loss_{dt}/100)\right)^{-1} \cdot \left(F_{gravity} + F_{wheel} + F_{drag}\right) \cdot v \tag{8}$$

F_{drag} contains the term v^2 making Eq. (8) a third-degree equation. Hence, Eq. (8) is solved as a function of each of the slopes defined in each segment, giving as result the array v. Then, it is possible to calculate the approximate time that the vehicle requires to circulate through the n^{th} segment through Eq. (9), where d_n is the distance of the n^{th} step. We are going to consider d_n as a constant value given by the user and equal to the length of the segments.

$$\Delta T = \frac{\Delta d_n}{v_n} \tag{9}$$

3.3. Coefficients Estimation

The coefficients C_{rr} and C_d are empirically calculated through the following experiment: the e-bike is ridden on a terrain with practically no elevation ($G = 0$) and the data is obtained through a GPS and stored. The previous equations can be simplified as follows:

$$F_{resist}[N] = F_{wheel} \cdot F_{drag} \tag{10}$$

$$F_{wheel}[N] = g \cdot W \cdot C_{rr} \tag{11}$$

$$F_{drag}[N] = C_d \cdot A \cdot Rho \cdot v^2 \tag{12}$$

Moments later, when a certain speed is reached, the pedaling is stopped until the bicycle finally stops. Using Eq. (10) and dividing by the total mass of the system (known value), it is possible to obtain an expression for the acceleration, as shown by Eq. (13).

$$a[m/s^2] = g \cdot C_{rr} + \frac{C_d \cdot A \cdot Rho}{W} \cdot v^2 \tag{13}$$

With the information obtained through GPS, and since the values of a and v are known, a linear regression is done between the two variables making it is possible to identify the position coefficient as the term given by gC_{rr} and the slope of the regression as $(C_d ARho)/W$. Since all the variables are known, it is possible to calculate C_d afterwards.

3.4. Optimization Algorithm

The decision making process to determine in what segments of the route the motor will operate, is done with Binary Particle Swarm Optimization (BPSO), an evolutionary optimization algorithm. It is inspired on the behavior of collaborative organisms' swarms and how they create trajectories. The swarm is represented by particles that use the obtained fitness information of all the particles to find the optimum value. This algorithm is based on the regular Particle Swarm Optimization (PSO) algorithm. PSO considers the potential solution to the optimization problem representing it by the i^{th} particle of spatial coordinates $x_{i,j}$, that was obtained when searching in the function domain through a vector speed or change rate denoted by $v_{i,j}$, where the subindex j moves along the coordinated of the D-dimensional space of the function domain. Each particle memorizes the value of its best fitness on the variable $P_{best,i,j}$ at the same time in which the whole swarm knows the value for the best global fitness on the variable $g_{best,i,j}$ (Kennedy & Eberhart, 1997). The position of the particles is updated with the following equations, where t represents the time instant:

$$x_{i,j}(t+1) = x_{i,j}(t) + v_{i,j}(t+1) \tag{14}$$

$$v_{i,j}(t+1) = \omega \cdot v_{i,j}(t) + c_1 R_1 \cdot \left(p_{best,i,j} - x_{i,j}(t)\right) + c_2 R_2 \cdot \left(p_{best,i,j} - x_{i,j}(t)\right) \tag{15}$$

The BPSO case is equivalent to the PSO algorithm but the components that move along the function domain take values of 0 or 1. In this sense, it is necessary to redefine how the particles are updated, understanding the concept of velocity as the probability of the j^{th} component of the particle varies its actual value (Lee, Soak, Oh, Pedrycz, & Jeon, 2008), and this is solved as shown by Eq. (16):

$$x_{i,j}(t+1) = \begin{cases} 0, & if\ rand() \geq S\left(v_{i,j}(t+1)\right) \\ 1, & if\ rand() < S\left(v_{i,j}(t+1)\right) \end{cases} \tag{16}$$

In this case, S(·) corresponds to the sigmoid function explained by Eq. (17), and evaluated with the velocity obtained from Eq. (15), to limit the magnitude between 0 and 1 and describing in this way the probability of change. The expression *rand()* is just a random number between 0 and 1.

$$S\left(v_{i,j}(t+1)\right) = \frac{1}{1+e^{-v_{i,j}(t+1)}} \tag{17}$$

Furthermore, the application considers the BPSO particles in a manner that the binary components indicate if the user must pedal (value of 0) of not (value of 1). Note that the dimension of the particle corresponds with the N partitions done at the beginning, where the j^{th} component of the particle corresponds to the j^{th} step of the trip. Then the function to be optimized is given by Eq. (18).

$$Y = \left(\left[\left(SOC_s - SOC_f^*\right) \cdot Q_{nom}\right] - \sum_{n=1}^{N} i_n \Delta T_n x_{i,n}\right)^2 \tag{18}$$

On Eq. (18), SOC_s is the available state-of-charge (SOC) at the beginning if the trip, while SOC_f^* is the desired amount of charge when arriving at the destination point, and Q_{nom} is the nominal capacity of the bicycle's battery, measured in (Ah). Thus, the first part of the Eq. (18) represents the energy that ideally is going to be employed for the trip. The summation represents the energy that is going to be used for a given pedaling profile, described by $x_{i,n}$. The estimated time in which the cyclist travels the $n-th$ step of the trajectory partition is given by ΔT_n (calculated with Eq. (9)). Finally, i_n is the electric current consumed by the motor on that segment of the route.

4. RESULTS

The following results were obtained through the simulation of the route between Plaza de Maipu and Plaza Italia, in Santiago, Chile, as seen on Figure 2. Using Google Earth it is possible to obtain the elevation profiles for the route to follow.

Figures 3 through 8 show the results for six different simulation scenarios for the same route using the proposed optimization algorithm. The black continuous line on these figures indicate the altitude above sea level of the route referenced to the starting point, obtained with Google Earth Elevation Profiles. The bars represent those segments in which the motor will be turned on, and the lack of bars indicate that the motor will be turned off. Since BPSO is a type of heuristic genetic algorithm the obtained solutions can be different. Furthermore, the solutions are considered to be reasonable within a certain range, in which the final SOC will not be less than the specified at the beginning of the simulation, since there are other environmental variables that escape from the focus of this model, such as: road signs, detours, or traffic, to mention a few.

Figure 2: Route and Elevation Profile.

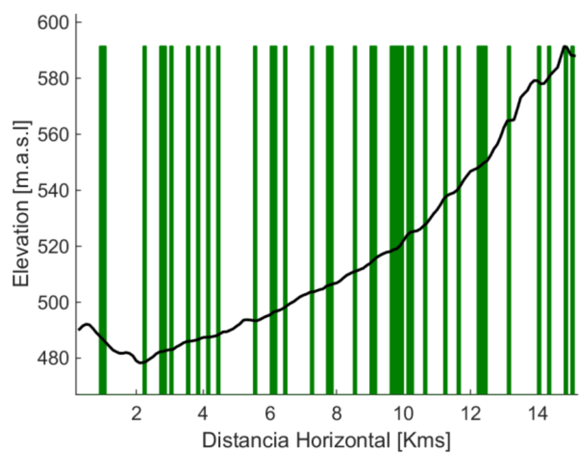

Figure 3: Utilization scheme for case #1.

Table 1 shows the results for different simulation scenarios, of the previous figures. The variable Q_{nom}, represents the nominal capacity of the battery, C_{ideal} is the theoretical capacity that should be consumed in the route, while C_{sol} is the estimated consumed capacity if the algorithm is employed. The column distance is equal to the length of each partition or segment in which the total route was divided prior to the optimization. It is important to mention that the motor is on or off during complete segments.

The size of the partition plays an important role since there is more precision on the solutions when the amount of segments is greater, however, this will translate into a higher computational cost. Also, it is important to remember that small segments can give solutions where the motor turns on and off over small distances creating a certain degree of discomfort for the user.

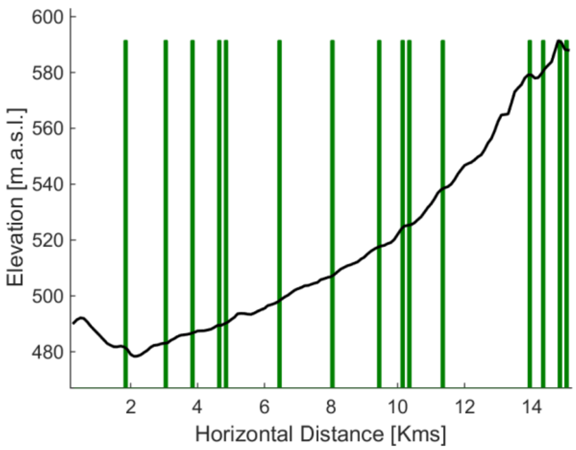

Figure 4: Utilization scheme for case #2.

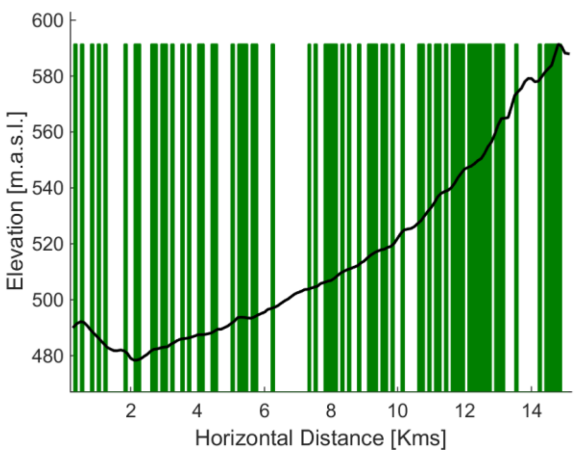

Figure 5: Utilization scheme for case #3.

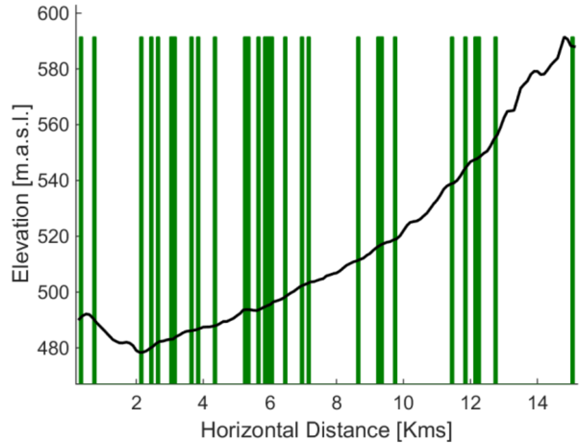

Figure 6: Utilization scheme for case #4.

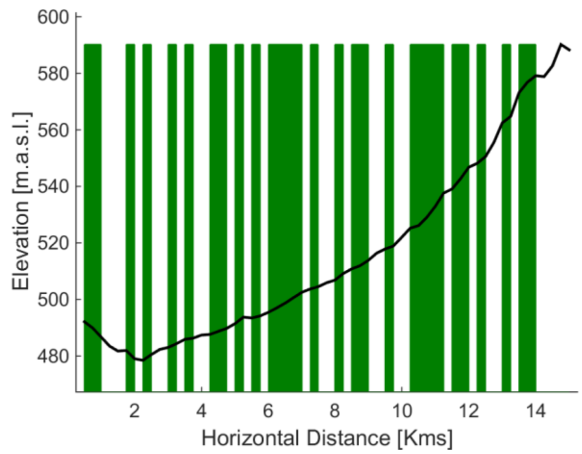

Figure 7: Utilization scheme for case #5.

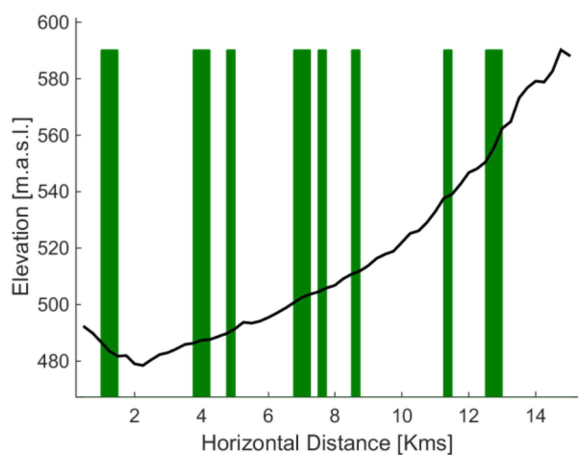

Figure 8: Utilization scheme for case #6.

Table 1. Simulation Results Summary

Case	Distance [m]	SOC_s [%]	SOC_f^* [%]	Q_{nom} $[Ah]$	C_{ideal} $[Ah]$	C_{sol} $[Ah]$
1	100	100	50	4	2	1.9906
2	100	100	80	4	0.8	0.7843
3	100	100	50	8	4	4.0122
4	100	100	80	8	1.6	1.5644
5	250	100	50	8	4	4.0302
6	250	100	80	8	1.6	1.6711

5. CONCLUSIONS

This paper proposed a methodology to manage the use of the available energy of an e-bike. The routes are characterized with an elevation profile that will be used as an input to an optimization algorithm that will assist the user and determine in what parts of the trip the motor will be on and in which parts will be off. This way, the user will arrive to the destination using only the desired amount of energy, and keeping the rest stored in the battery.

The optimization algorithm delivers different solutions for the same route, and it is possible to modify certain parameters, for example the distance of the segments in order to find a more convenient solution regarding the preferences of the user, and giving continuity to those segments where the motor is on.

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