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Electric Vehicle Parameter Identification

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Abstract

This work describes a method developed to simplify and reduce the cost of the standardized testing required to measure the energy consumption of electric motorcycles before they are sold on the Swiss market. The robust algorithms for estimating four characteristic parameters of electric two-wheelers are based on a linear dynamics model that is considered to be as simple as possible yet as complex as necessary to characterize the vehicles. The model equations are investigated analytically for their ability to find unique solutions, and it is shown that multiple solutions may exist. The algorithms are tested for their ability to handle various data frequencies, levels of noise, and initial guesses. Ultimately it is found that these methods effectively enable the use of simulation models trained on real-world driving to run mandated standard test cycles in place of expensive dynamometer testing to estimate on-road energy use.

Keywords: modelling, simulation, optimization, scooter, standardization

1 Introduction

The demand for electric two-wheeled vehicles is growing rapidly together with the number of new models entering the market. By 2016 almost 500 million electric two wheelers are expected to be on the road globally [1]. The manufacturers of these light electric vehicles (e-bikes, e-scooters, e-motorcycles) will have to meet regulations for introducing new vehicles; in particular, the on-road energy use will be required to be quantified using standardized dynamometer tests. The average sales price for an electric scooter in Switzerland is roughly 7500 CHF [2] which means that standardized dynamometer testing that costs more than 10’000 CHF per model [3] can have a significant impact on importer margins.

This paper explains how collecting on-road driving data and applying numerical parameter identification methods can substantially reduce the cost of standardized testing for new vehicle models while producing (more useful) real-world energy use information. The methods presented here have been applied to generate standardized energy use and driving range information for electric motorcycles sold on the Swiss market [4].

In addition to accurately emulating standardized dynamometer test procedures, the methods presented here can be applied to improve real-time electric vehicle range estimation procedures, allowing fleet managers and drivers to perform on-the-fly trip optimization, and for informing drivers about their options for reducing energy use.

1.1 Previous work

Many methods of simulating a vehicle over a particular driving cycle have been developed. The simplest 'linear dynamics' or '1-dimensional' class of models based on motive and resistive forces acting on a vehicle are surprisingly adequate at explaining much of a vehicle's on-road energy use, and have been therefore selected as the method used to model the vehicles in this work [5], [6].

Past efforts aimed at identifying vehicle parameters have focused on finding the aerodynamic coefficient while when vehicles are coasting down and hence other forces may be negligible [7], [8]. Other approaches have been to use heavily instrumented vehicles with many data streams [9], or very computationally intensive algorithms to identify parameters [10]. The limitations to these approaches are that they do not identify all of the loss parameters, they require expensive sensing equipment, and they require a significant amount of time and/or expensive computing resources.

1.2 EV Parameter Identification

This section highlights the uniqueness and describes the methods developed for electric vehicle parameter identification. The approach presented here offers several key advantages over previous efforts:

1 A grey-box model capturing all vehicle losses allows physical meaning to be interpreted from the identified parameter values,
2 The input to the algorithm relies on data from very few sensors with a relatively low sampling frequency saving system cost,
3 Data may be used without extensive pre-processing saving computing effort and algorithm complexity,
4 Various efficient methods for numerical optimization can be applied to solve for the loss parameters, each executing without significant computational effort.

The first step in the parameter identification process is the development of a physical model. This paper focuses on two-wheeled electric vehicles, but the methods developed here can also be applied to treat other types of electric vehicles. For two-wheeled vehicles, the model is characterized by the free body diagram shown in Figure 1.

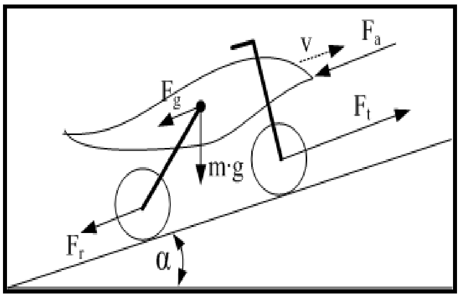

Figure 1: Electric motorcycle force balance

The forces acting on the electric motorcycle are balanced in Equation (1) where the total mass of the vehicle and rider m_v is multiplied by vehicle's acceleration $\dot{v}(t)$ and equated to the various forces described acting on the vehicle described by Equations (2) to (5).

$$m_v \cdot \dot{v}(t) = F_t(t) - \left(F_a(t) + F_r(t) + F_g(t)\right) \qquad (1)$$

Rolling resistance F_r in Equation (2) depends on the coefficient of rolling resistance c_r (which in turn depends on various factors relating to the vehicle's tires), the total mass of the vehicle, and the angle of ascent/descent α. The vehicle's velocity v(t) affects the dynamic characteristics and hence resistance of the tire [11], [12], but in this model these effects are not considered to be significant and the rolling resistance coefficient is assumed to be constant.

$$F_r(t) = c_r \cdot m_v \cdot g \cdot \cos(\alpha), abs[v(t)] > 0 \quad (2)$$

The force exerted by gravity F_g shown in Equation (3), which depends on vehicle mass and the angle of ascent/descent α,

$$F_g(t) = m_v \cdot g \cdot \sin(\alpha) \qquad (3)$$

Aerodynamic drag F_a is shown in Equation (4), which depends on the density of air ρ_a, the frontal area A_f (highly variable for two-wheeled vehicles), the coefficient of drag c_d (also highly variable) and vehicle speed. The frontal area and coefficient of drag will be lumped as $C_{aero} = A_f \cdot c_d$.

$$F_a(t) = \frac{1}{2} \cdot \rho_a \cdot C_{aero} \cdot v(t)^2 \quad (4)$$

The traction force F_t provided by the motor's torque is defined in Equation (5). While there are several approaches to modeling electric machines [13], the approach taken in this work considers the instantaneous traction power P_t to be proportional to the electrical power P_{el} supplied to the motor by efficiency η.

$$P_t(t) = P_{el}(t) \cdot \eta = F_t(t) \cdot v(t) \quad (5)$$

It is important to note that the braking force that would normally appear in Equation (5) is not considered in this model, which vastly simplifies data acquisition at the expense of some accuracy identifying physically meaningful parameters. Using this model the four parameters listed in Table 1 can be identified from the data set.

Table 1. Parameters found using PI methods

Physical parameter	Variable	Low	High	Unit
Vehicle mass	m_v	30	400	kg
Rolling resistance coefficient	c_r	0.0001	0.05	-
Lumped aerodynamic coefficient	C_{aero}	0.005	1.5	m^2
Powertrain efficiency	η	0.4	0.99	-

To estimate the parameters numerically the algorithm shown schematically in Figure 2 was used. It was by implemented using MATLAB's optimization toolbox to minimize the least-squares difference between measured and simulated power shown in Equation (6) for each point k in the driving cycle until the optimal parameters were found.

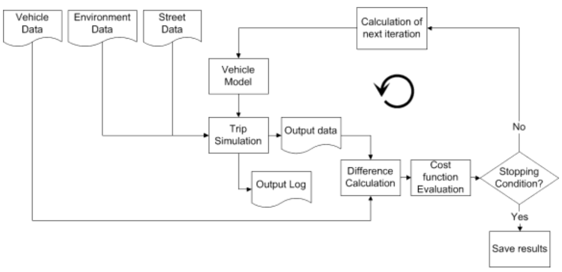

Figure 2: Parameter identification algorithm

$$f(x) = \sum_{x=1}^{k} \sqrt{(P(x)_{sim} - P(x)_{meas})^2} \quad (6)$$

Several other methods of finding optimal parameters are possible and were explored before settling on this algorithm [14]. The detail of this selection process is beyond the scope of this paper.

2 Analytical Solution

The equation of motion for the electric motorcycle as described by Equation (1) can be solved analytically as homogenous polynomials in parameters m_v, C_{aero}, and η. This means that if (m_v, C_{aero}, η) is a solution to Equation (1), then $k(m_v, C_{aero}, \eta)$ is a solution as well, where $k \in \Re$. This means that of all the four unknown parameters, we can only obtain a unique solution for the rolling resistance coefficient c_r analytically. To de-homogenize Equation (1), additional measurement data is required. An example would be to measure the vehicle mass m_v to determine the k value.

To solve for the parameters we rewrite Equations (1) to (5) in the normal form

$$h_\theta(\vec{x}) = x_0 + x_1\theta_1 + x_2\theta_2 + x_3\theta_3 + x_4\theta_4, \quad (7)$$

where the monomials θ_i are unknown parameters of the form:

$$\begin{aligned} \theta_1 &= m_v, \\ \theta_2 &= C_{aero}, \\ \theta_3 &= m_v c_r, \\ \theta_4 &= \eta, \end{aligned} \quad (8)$$

and its coefficients x_i as functions of the measured data sets ($v, \dot{v}, \alpha, P_{el}$) such that

$$\begin{aligned} x_0 &= 0, \\ x_1 &= \dot{v} \cdot v + g \cdot v \cdot \sin(\alpha), \\ x_2 &= v^3, \\ x_3 &= g \cdot v \cdot \cos(\alpha), \\ x_4 &= -P_{el} \end{aligned} \quad (9)$$

Assuming that we have gathered m data sets ($m > 4$) over a course of time, then for each of these data sets we would have the following system of normal equations:

$$\begin{aligned} h_\theta(\vec{x}^{(1)}) &= 0, \\ h_\theta(\vec{x}^{(2)}) &= 0, \\ &\vdots \\ h_\theta(\vec{x}^{(m)}) &= 0. \end{aligned} \quad (10)$$

The normal equation method strives to minimize the cost function in Equation 11 which is a normalized way of re-writing Equation 6 [15].

$$J(\theta_0,...,\theta_m) = \frac{1}{2m}\sum_{i=1}^{m}(h_\theta(x^{(i)}) - y^{(i)})^2 \quad (11)$$

for $i = 1,\ldots, m$ and in our case $y^{(i)} = 0$.

The solution to Equation (11) can be solved using singular value decomposition. We first rewrite the system of equations (10) in the matrix form

$$[X]\vec{\theta} = \vec{0}. \quad (12)$$

Now pre-multiply Equation (12) by the transpose of the design matrix $[X]$ to obtain

$$[X]^T[X]\vec{\theta} = [A]\vec{\theta} = \vec{0}. \quad (13)$$

Next, decompose the matrix $[A]$ using singular value decomposition to obtain

$$[A] = [U][\Sigma][V]. \quad (14)$$

$[U]$ and $[V]$ are 4 x 4 orthogonal matrices, and $[\Sigma]$ is a 4 x 4 diagonal matrix of the form $[\Sigma] = diag(\sigma_1,\cdots,\sigma_4)$ with $\sigma_1 \geq \cdots \geq \sigma_4 \geq 0$. The σ_i's are called the singular values and columns of $[U]$ and $[V]$, denoted as u_i's and v_i's are known as the left and right singular vectors respectively.

The solution to the Equation (11) turns out to be the right singular value of $[A]$ that corresponds to the smallest singular value. Therefore, we can solve for the four parameters using

$$\begin{Bmatrix} m_v \\ C_{aero} \\ m_v c_r \\ \eta \end{Bmatrix} = k \cdot v_4. \quad (15)$$

The result of this analytical solution method is that a unique solution may only be obtained for the rolling resistance coefficient c_r due to the physics of the problem. The other three parameters have non-trivial solutions and hence multiple least-cost solutions will always exist. A unique solution can be obtained should one parameter be fixed using a simplifying assumption.

3 Numerical Solution Testing

This section describes how the numerical parameter identification method was developed and fine-tuned. In this process particular emphasis was placed on answering four main questions:

1. If fake driving data is generated using the linear dynamics model in Equation (7) with a specified parameter set, will the PID algorithm find this exact set?
2. How robust is the optimization method with respect to variation in the initial guesses?
3. Does sampling frequency play a big role in the accuracy of the algorithm?
4. How severely does signal noise confound the algorithm?

This validation effort is one of the major results of this work; hence the depth that this section reaches in explaining what was done.

3.1 Known parameter benchmarking

The first test requires 'fake' driving data to be generated based on the linear dynamics model in Equation (7). If the algorithm is effective, the identified parameters will be identical to the parameter set specified in Table 1 which was used to with Equation (7) generate the 'fake' data. This of course makes the implicit assumption that the real world can be well-represented by the model, something that has been well-documented in the literature [16], [17].

Figure 3 shows the results of running three different input cycles for the MIT EVT`s eSuperbike vehicle [18]. It is clear from all three duty cycles that the simulation model based on the identified parameters is able to accurately match the 'measured' data generated using the same parameters. In other words, the algorithm appears to pass its first test.

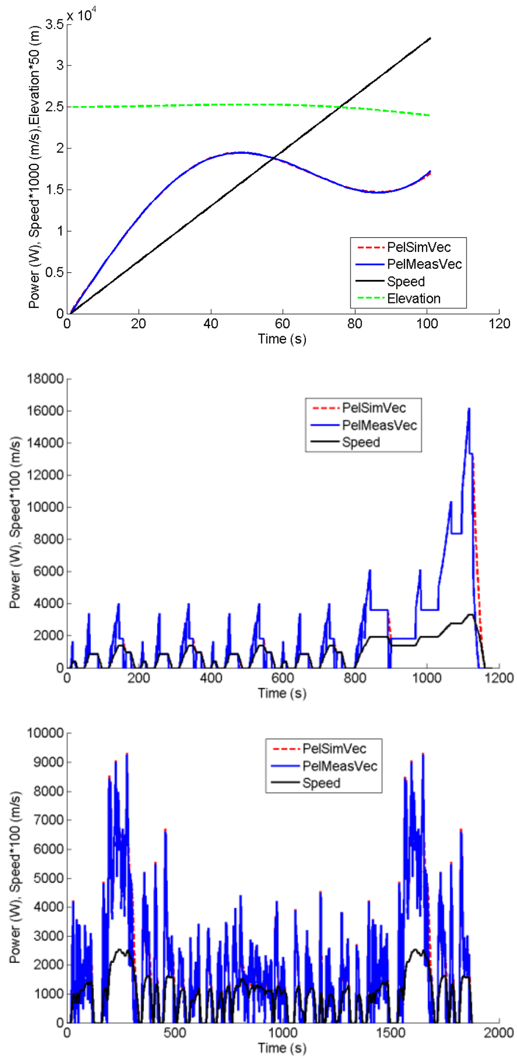

Figure 3: Parameter identification for three drive cycles. Top: Single acceleration event up and down a hill; Middle: New European Driving Cycle NEDC, Bottom: FTP-75

The convergence process is shown in Figure 4 demonstrating how the identified parameters settle during the optimization.

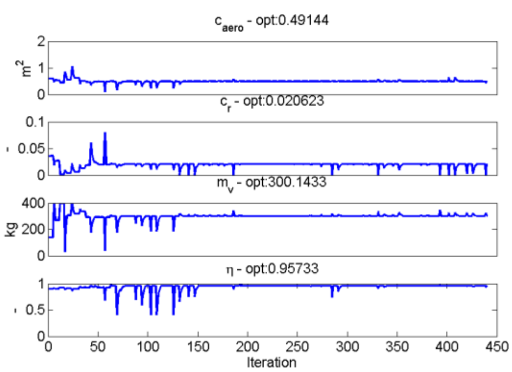

Figure 4: Convergence for the identification of parameters for the FTP-75 driving cycle

The parameters found for each input cycle are compared with the true parameters in Table 2. The difference between the known and identified parameters is most pronounced for the rolling resistance coefficient. It is also interesting to note that the difference between the true and identified energy increases as the cycle becomes closer to real world driving, as calculated by comparing simulated results using true and identified parameters for the standard driving cycles. This observation is important because it means that very stylized, repetitive standard cycles such as the NEDC will be easier to simulate than more real-world cycles such as the FTP-75. As well, this implies that it may be easier to identify physically meaningful parameters for small subsets of real-world driving, which is a useful observation for future research.

Table 2: known parameters, estimated parameters, error for all four drive cycles

	Known	Single	NEDC	FTP-75	Ave. Error
m_v	272	291	299	300	9%
c_r	0.025	0.041	0.025	0.02	15%
C_{aero}	0.41	0.36	0.48	0.49	8%
η	0.9	0.98	0.98	0.95	8%
Cycle energy error		1%	10%	12%	

3.2 Sensitivity to initial guess

To answer the next question a series of tests with different initial guess parameters as shown in Figure 5 were run on simulated/fake test data (generated as in Section 3.1). The blue curve shows the initial guess for the parameter for each trial, the green curve represents the true parameter value (and is hence static), and the red curve shows the parameter which found after the optimization converged. The 256 tests were run for every possible combination of four parameters at four levels each.

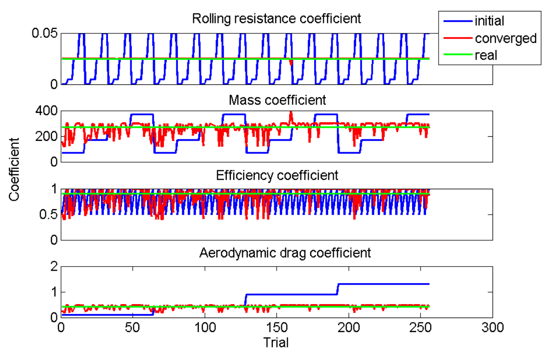

Figure 5: Initial guesses, convergence

From this analysis it is clear that the initial guess has an impact on the converged parameter which is a result that was anticipated based on the discussion of the analytical solution in the previous section. The variation in the model's ability to find the true parameter value (its error) was most significant for mass and efficiency, two parameters which explain a large amount of the variation shown in Figure 6.

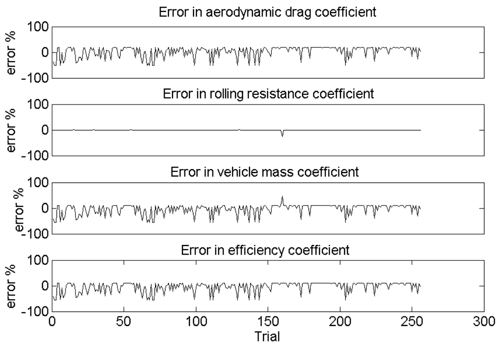

Figure 6: Parameter estimation error over the NEDC driving cycle

This high degree of variability in identified parameters may at first seem like a discouraging result, but Figure 7 shows that there is surprisingly little error in the energy estimation over the driving cycle. This result was generated (as in Table 2) by comparing the true parameter versus the identified parameter results at predicting standard cycle energy use results. This means that even though multiple solutions for the model parameterization exist, as predicted using the analytic method, the optimization nevertheless often converges to a solution which is nearly 90% accurate at describing the energy use over the standard driving cycle.

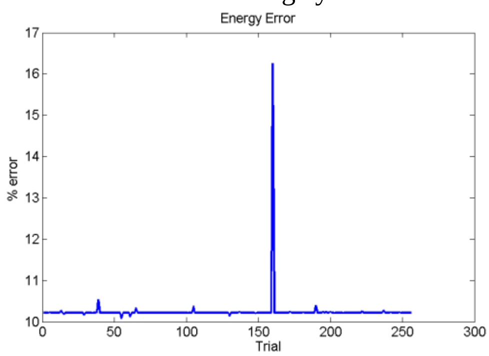

Figure 7: Energy estimation error over the NEDC driving cycle (the spike in the error is caused by a solution that converges to the maximum weight boundary)

This section has shown that the method presents a challenge in using the identified parameters to represent a meaningful physical value, but for the purposes of this work does not impede the simulation of standard cycle testing. One major source of this error is the systematic over-representation of physical parameters due to the decision not to consider braking energy in the model equations.

3.3 Sensitivity to sampling frequency

In order to estimate the impact of sampling frequency on how well the algorithm can estimate parameters the frequency of simulated/fake test data was varied from a slower 0.1Hz to the standard 1Hz to a faster 10Hz. The results of this test are shown in Figure 8 which clearly demonstrates that for the NEDC driving cycle, the higher the sampling frequency, the lower the average error. This is relevant when considering the cost and bandwidth limitations associated with telematics data logging systems [19].

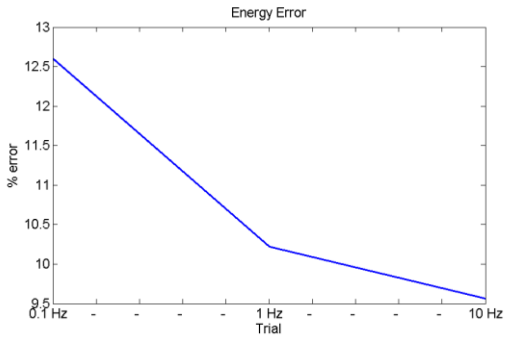

Figure 8: The error between the predicted and the true values gets lower as sampling frequency gets higher, and the error is more pronounced as the sampling frequency gets lower

3.4 Sensitivity to noise

The goal is to develop algorithms which can be implemented in the real world with reasonable tolerance to noise caused by sensor and communication link. To test how sensitive the algorithms are, Gaussian white noise was added to the power measurement signal in varying levels (from no noise to a noise/signal ratio of 3, 9, and 27). Figure 9 shows the highest level (N/S=27) of noise applied to the NEDC driving cycle, which highlights the challenge presented by noise to a least-squares minimization algorithm.

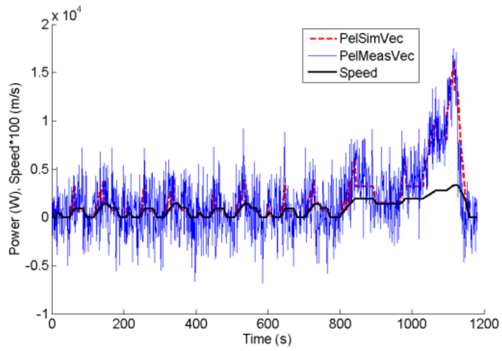

Figure 9: N/S = 27 applied to input signal before parameter identification

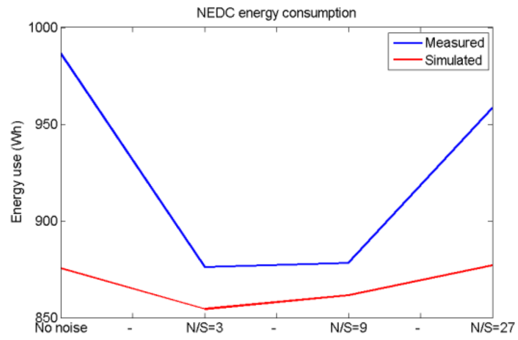

Figure 11: Model error decreases as Gaussian white noise increases due to negative power events caused by noise

A disconcerting result is shown in Figure 10 where it can be seen that as the amount of Gaussian white noise increases, the optimal parameters converged upon by the algorithm vary significantly. This means that noise has a significant impact on the algorithms ability to find an optimum, and should therefore be reduced as much as possible during measurement. More than this qualitative statement cannot be made at this stage.

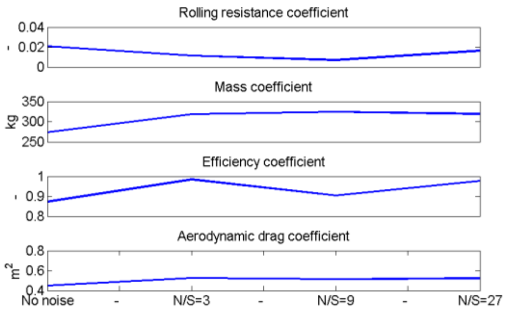

Figure 10: Large variation in optimal parameterization for mass and efficiency coefficients caused by noise

One interesting observation shown in Figure 11 is that a little bit of noise (N/S=3 and 9) actually improves the model's accuracy. This is unfortunately not a result of better parameterization, but rather that the measured energy is moving closer to the simulated energy as noise increases and negative power noise reduce the measured energy use. The added noise does not significantly change identified parameters but does decrease the 'true' cycle energy significantly due to negative power events which drives the error down. Note that 850 W-h for the NEDC cycle corresponds to an equivalent fuel consumption of about 0.8L/100km.

4 Results

The main objective of this work was to develop a method to find e-motorcycle characteristic parameters from real-world data and use them to simulate vehicle energy consumption for a standard test cycle. The quality of the developed algorithm is tested in this section by comparing simulated results using identified parameters with energy consumption measured on a dynamometer for the same NEDC test cycle.

The measured and estimated energy curves in Figure 12 were generated based on real-world driving done in and around Lugano, Switzerland on a Quantya 'Strada' electric motorcycle. An important feature of the time-series power plot is that due to sensor failure error, some energy use was clearly not recorded, highlighted by the ellipse which shows the motorcycle moving without drawing any power at all (an extremely unlikely scenario, even while travelling downhill).

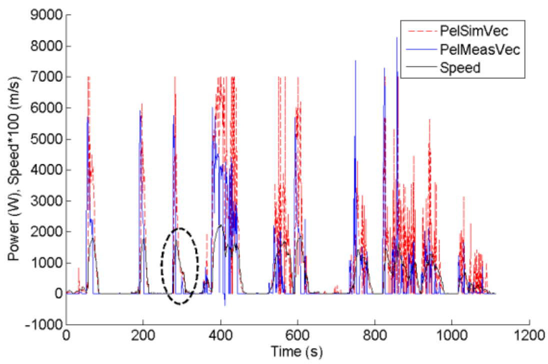

Figure 12: Training set for the Quantya Strada model with prominent sensor error (marked with dashed oval)

The simulated energy for this trip is 81% higher than the measured energy after integrating the simulated and measured power signals, a rather large discrepancy which can be mostly explained by the sensor error. The parameters identified for this larger, more powerful motorcycle are shown in Table 3.

Table 3: Quantya Strada identified parameters

Parameter	Manufacturer Estimate	Identified	Unit
m_v	140	110	kg
c_r	0.0001	0.04	-
$A_f \cdot c_d$	0.6	0.8	m^2
η	0.9	0.95	-

Thankfully when the parameters identified from real-world driving are used in the model running a standard NEDC cycle shown in Figure 13 there is very good agreement between the simulation and the measured value, with an energy difference of only -12%. This good agreement is in part due to the fact that the optimization finds parameters at the limits of the parameter values which were selected to constrain the optimization to physically meaningful values. If these limits are modified, the agreement changes dramatically. This shortcoming is not always present when using this method but unfortunately due to the holes in the available measured data the results that are presented here were subject to it. As a follow-on project, nine other electric two-wheelers were measured and the results were received with satisfaction by the manufacturers displaying vehicles at the NewRide event at the SwissMoto'11 in February 2011. The other vehicles measured and analysed often converged to a solution not at the parameter limits.

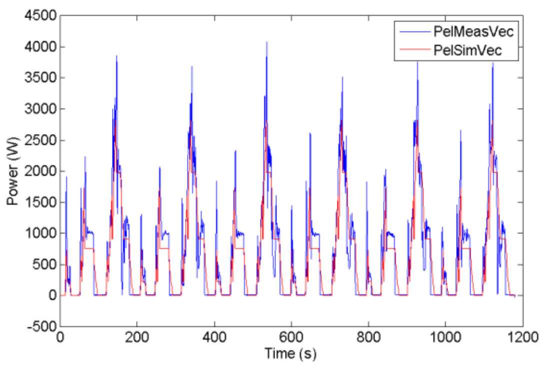

Figure 13: The identified Quantya model has a very good fit to standard NEDC cycle measurements performed on a dynamometer

5 Conclusions

The results of this work have shown that:

1. Parameters for a simple grey-box model of an electric vehicle can be identified using a method which applies advanced algorithms to a large set of real-world data,
2. The results can be used to accurately predict electric vehicle energy use over standard cycles,
3. The numerical optimization algorithms are sensitive to initial conditions as predicted by the analytical solution,
4. The algorithm is sensitive to sampling frequency, however not to the degree which impedes its application for standard cycle analysis,
5. The algorithm is sensitive to noise and the cleaner the signals the more repeatable the result is.

Real world energy use is inevitably higher than what standard cycles predict, which presents a rich area for further work based on the foundations presented in this paper.

6 Applications and Extensions

Several further applications are possible using extensions of the methods developed here, such as

- improving electric vehicle range estimation,
- allowing on-the-fly fleet monitoring and optimization (i.e. predicting relative weight changes, highlighting systematic vehicle losses),
- enabling accurate on-cue driver feedback when physical parameters indicate performance loss (i.e. flat tires, powertrain problems, etc.).

These extensions will be explored in greater detail in future work.

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