Personalised Controller Strategies for Next Generation Intelligent Adaptive Electric Bicycles

Lorenzo Stilo, Heinz Lugo, Diana Segura Velandia, Paul P. Conway, *Senior Member, IEEE*, and Andrew A. West, *Member, IEEE*

***Abstract*— Air pollution and increasing traffic congestion means the current way of navigating through a city needs to be rethought. One of the possible solutions is to move away from internal combustion engines and embrace electric and hybrid vehicles. Electric Bicycles can offer an alternative to traditional modes of transport and support an environmentally friendly way to navigate an urban environment, with the benefit of encouraging physical exercise. There are still several issues that constrain a large-scale acceptance of Electric Bicycles, including the need for personalised controller strategies and the energy efficiencies. Current strategies do not include any analysis of rider's capabilities, physiological factors or pedalling techniques. The research outlined in this paper involved 30 participants that volunteered to take part in an *Incremental Sub-Maximal Ramp Test* with the aim of understanding and quantifying pedalling characteristics and demonstrating that a better motor controller strategy tailored towards individual requirements is possible. *Gender* and *Cycling Experience* were the most prominent factors that differentiate the capabilities of the population. Three novel controller techniques (i.e. *Fixed Percentage*, *Torque Filling* and *Real-Time Power mapping*) are analysed and presented as innovative methods for next generation personalised controller strategies for Electric Bicycles.**

***Index Terms*— Electric bicycles, electric vehicles, energy efficiency, electric motor controller strategies, pedalling techniques, personalisation, rate of perceived exertion, torque filling.**

I. Introduction

Society is aware of the need for sustainable and environmentally friendly transportation [1]. However, convincing commuters to choose an electric bicycle (e-bike) and / or public transport over the comfort and convenience of their automobile is challenging. Nevertheless, the push towards healthier lifestyles [2] and the concerns over the quality of the air within cities leading to bans on diesel transport [3] requires analysis of alternative methods of moving around the urban environment [4]. Although there has been a sustained growth since 2005, particularly in the far east [5], by 2020 e-bike sales are expected to approach $10.8 billion [6] [7]. This situation has been mainly due to government policies that either promote the use of e-bikes [8], [9] or discourage the use of automobiles [10] coupled with an increasing environmental awareness [11].

Manuscript received May 8, 2019; revised March 6, 2020 and April 22, 2020; accepted June 26, 2020. Date of publication July 28, 2020; date of current version November 29, 2021. This work was supported by the BioEngine: a Ford eBike Motor Control System funded by the Ford Motor Company University Research Programme (URP) and U.K. Engineering and Physical Sciences Research Council (EPSRC) Award (Adaptive Informatics for Intelligent Manufacturing) under Grant EP/K014137/1. The Associate Editor for this article was A. Amditis. *(Corresponding author: Lorenzo Stilo.)*

The authors are with the Wolfson School of Mechanical, Electrical and Manufacturing Engineering, Loughborough University, Loughborough LE11 3TU, U.K. (e-mail: l.stilo@lboro.ac.uk).

Digital Object Identifier 10.1109/TITS.2020.3009400

Although users do acknowledge e-bikes as a mean to overcome issues with their fitness levels, to make commuting by e-bike a viable and regular option, they are faced with uncertainty in the e-bike's autonomy (i.e. range, recharging stations, ease of charge). This issue is significant as reported in the study conducted by Cappelle *et al.* [12], which showed that even after using e-bikes for a considerable period of time (i.e. 7 weeks) and noting the benefits (considerable less time spent in cars and traffic congestions) only 3% of the users ended up buying one. The increase in e-bike autonomy and associated efficiency is one of the main problems regarding the widespread adoption and use of e-bikes. Until this is achieved, the common view of e-bikes as either leisure vehicles or viable means of transportation restricted to regular cycling enthusiasts will continue.

One of the characteristics that affects the efficiency of e-bikes is the controller strategy governing motor power delivery [13]. Although there is a considerable amount of literature and experience dealing with efficient motor drives [14]–[16] the influence of the riders' pedalling capabilities (e.g. rate of torque application, maximum torque location [17]) and physiological characteristics (e.g. age, sex, experience [18]) have not been directly addressed to date. Focusing solely on the magnitude of torque is an easy implementation but it has major limitation as it amplifies the human inefficiencies and does not take into account human capabilities. The inclusion of some physiological characteristics in the control loop has been reported [19]–[21] mainly using heart rate as a reference level of cyclist effort hence controller support level. However, heart rate presents difficulties in determining a specific strategy for each individual user due to its variability as a result of factors such as absolute and periodic changes in fitness levels, fatigue, weather or stimulants (e.g. coffee, energy drinks, food and alcohol) consumption [22].

In this paper three novel controller strategies for the next generation of adaptive e-bikes are presented, these original strategies are based on the pedalling characteristics observed from 30 participants, divided into 4 groups (i.e. not cyclists, recreational, commuter, competition) subject to an incremental submaximal ramp test. The research builds on established controller strategies principles (e.g. proportional, fuzzy logic [23]) and integrates the strategies to accommodate the test results. Having the possibility to compare gold standard pedalling characteristics, i.e. those exhibited by competition cyclists, with those observed for the other groups allows the identification of which performance characteristics the controller should replicate for improved performance and better support of cyclists' requirements.

The main goal of the research outlined in this paper is the adaptation of current controller strategies to include the pedalling characteristics observed in the general population. Note: dynamic modelling and real-world implementation of these strategies will be reported in further publications by the authors.

II. Current State of the Art

There are three types of strategies currently adopted to control the amount of power assistance given by the electric motor on an e-bike: *fixed gain*, *constant speed* and *constant effort* [24]–[28]. Out of the three, fixed gain is the most used on commercial e-bikes.

In the *fixed gain* strategy, the assistance level is set as a fixed percentage of the torque input by the rider, commonly set to 70%, 150% and 230% [28], [29]. Given the fluctuation of torque across the pedal cycle, this type of control tends to amplify torque ripple and speed fluctuation and can lead to situations where the net power (i.e. combined power between the rider and the motor) is not enough to overcome the resistive load on the rider (e.g. aerodynamic drag and rolling resistance [30]). The *fixed gain* strategy is heavily dependent on cycling cadence and many experience delays in power deliveries especially at high cadences. Moreover, the current fixed gain strategy requires, in the large majority of the cases, the rider to choose their gain level, trusting in the ability of cyclists to self-assess their capabilities.

Constant speed controllers depend upon either detecting the movement type experienced (e.g. acceleration, constant speed) or the response to a disturbance from a horizontal road condition. It attempts to maintain the speed constant (usually based on a throttle or the rider's cadence) independent of the environmental conditions (i.e. road incline, surface resistance, wind resistance) adjusting the motor contribution accordingly [31]–[33]. The simplicity of the hardware implementation (i.e. only requires torque transducer and cadence sensor [34], [35]) is an advantage of these types of controllers.

Instead of focusing on the actual value of the torque and cadence, a Fuzzy Logic Control (FLC) [16] implementation using the behaviour of the variables to determine the movement type has been discussed in the literature. Controller response is fixed by constant multiplying factors of the motor current (i.e. output torque) for each movement type [15], [36]. Inferences to determine the movement type are based on assumptions such as a decrease in speed and increase in torque during inclines, although such a pattern of behaviour is not unique to inclines. However this method: (i) is impacted by regulations (i.e. EU laws require electric assistance to be delivered without a throttle [37]) and (ii) could result in unstable operation as it takes control away from the rider in attempting to fix a constant speed for the bicycle. Although some authors highlight that the motor contribution [31] can be varied to account for the user's fitness level and experience, there is no evidence presented in their publications on how this should be implemented [31]–[33].

Most of the *constant effort* e-bike controller implementations focus on maintaining a physiological variable (e.g. heart rate) at a constant level irrespective of the environmental conditions encountered by the cyclist. Using heart rate based dynamic models some authors predict the heart rate response to a particular load. The motor contribution required is then defined as the difference between the power input by the rider and the power set for a particular heart rate according to the model [19], [38]. Unfortunately, heart rate dynamics are known to be subject to uncertainties due to intra-subject differences and other non-linearities (e.g. oscillations and unpredicted trends possibly connected to physiological factors) not directly influenced by the physical effort which can limit accuracy of control strategies [19], [39]. Instead of using heart rate as the physiological variable Nagata *et al.* [40] used oxygen uptake to measure the physical effort of the rider. Based on deriving a value for effort from oxygen uptake values, motor support was provided to increase or decrease power output accordingly. Although oxygen uptake can be used as an accurate determinant of physical performance, its measurement involves complex hardware more suited to a laboratory environment [41]. Furthermore, the authors have fixed the effort/cadence model only for a small set of users for which the preferred pedalling cadence was 65 rpm and hence is not representative for other user types. According to Abbiss *et al.* [42] the optimal cadence for cycling depends on factors such as the distance to travel, fatigue and personal preference (and can range between 70 and 120 rpm).

Although there are multiple strategies reported in the literature to determine the most adequate power motor assistance, there is a general tendency to fix the motor contribution values ignoring the effect of the cyclists' characteristics on the system. In addition, whenever the cyclist is taken into account, the variables used to measure their influence are either highly uncertain or difficult to measure. The results outlined in this paper indicate that without adding any extra sensors to the current most common design and by considering some non-invasive physiological information it is possible to deliver a personalised motor controlling strategy that can deliver a better riding experience.

III. Incremental Submaximal Ramp Test

A. Previous Work

The purpose of the motor and controller on an e-bike is to complement the power input by the rider [10], allowing him/her to increase the travelling speed and/or ride for longer distances whilst reducing the effort required. However, there is no agreement on how much power the motor should contribute throughout the pedal stroke and no indication of the availability of different strategies (i.e. designed for distance, speed, acceleration) supported by controllers. Common approaches include: (i) Providing a fixed percentage of the rider input power [15] and (ii) Providing a varying torque aid as a function of travel speed [43]. Individual rider characteristics (e.g. age, fitness level, performance desires and requirements) are often ignored.

Academic literature offers few examples of studies aiming at understanding possible implementations of novel motor controllers: few studies focus of novel techniques i.e. using Fuzzy Logic [15], [16] or attempting to counterbalance environmental disturbances [31]–[33]. Limited studies have looked at energy harvesting [44] and others have mainly focused on novel hardware applications [45], [46]. Very little research has been undertaken to include human performances and physiological factors in the controller strategy.

Many research reports focused on improved cycling performance exist but only a few studies investigate a connection with electric bicycles. Their aim is usually to aid coaches and elite athletes with technical analysis of their performance. Three main tests can be identified in this space: performance-oriented studies; technique-oriented studies and fatigue-oriented studies. Performance-focused studies usually target determining factors as functional threshold power (FTP, i.e. power a cyclist can sustain in 1h) or critical power (CP, i.e. power output that will result in exhaustion after 1h) and various studies use VO_2 Max to determine efficiency [47]–[49]; these tests do not target a wide population and are often invasive. Technique-focused studies mainly address four factors: cadence; torque; balance and rider's position [50]–[52]. Often these studies tend to contradict each other [53] and very little has been written on rate of power application or correlation with physiological factors. Finally, fatigue focused studies look mainly at how fatigue impacts technique factors [54], [55]. This study aims at addressing the whole bicycle user's population and was designed to be as inclusive as possible. This led to the exclusion of tests like ride-to-exhaustion and VO_2 Max tests. The study attempts to understand pedalling characteristics for cyclists with different backgrounds and how they relate to physiological factors.

B. Design of Experiments

As shown in Fig. 1, the aim of implementing a test protocol is to determine how much power the motor should deliver while taking into account the rider's age, sex, fitness level and cycling experience. As highlighted by Cappelle *et al.* [12], one way to increase interest on e-bikes is the personalisation for different users.

A good test protocol should exhibit: (i) Validity (i.e. similarity to the situation it is trying to replicate), (ii) Reliability (i.e. repeatability between tests when no change has been made) and (iii) Sensibility (i.e. the ability to detect small but meaningful changes in the measured variables) [56]. Out of the three types of test protocols related to cycling (i.e. *aerobic, anaerobic, competition simulation*) *aerobic* test protocols replicate the demands observed during commuting

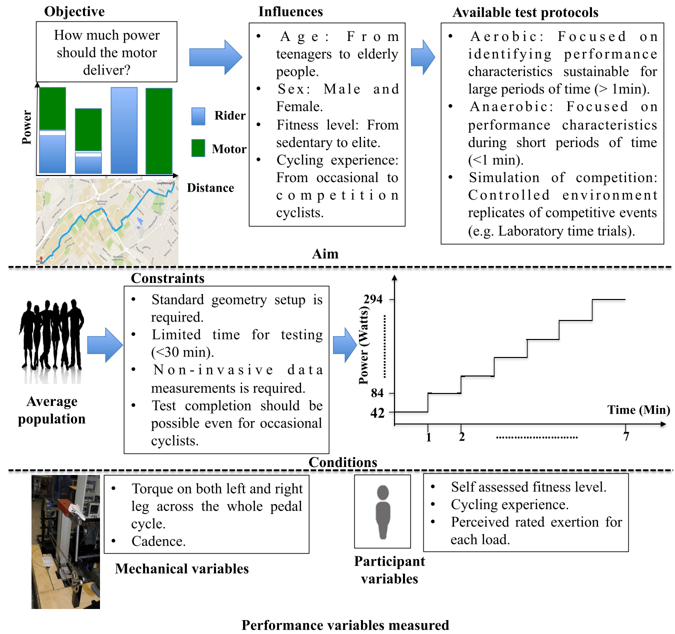


Fig. 1. Test protocol definition.

or leisure riding (see Fig. 1). Common commuting distances (e.g. 5 to 15 km) [12] can involve periods of time up to one hour and since they are neither a race simulation or maximum efforts, aerobic type testing is valid [57]. Aerobic tests (e.g. the *incremental test* where the participant is asked to sustain an increasing power output over time) have been shown to produce random errors of $\sim$1% and have been successfully used to detect changes of $<$1% [56].

Although aerobic tests can be used to quantify performance variables under similar conditions experienced on a common e-bike ride/commute, typical load and termination criteria reported in literature (e.g. *ride to exhaustion* [58]) are appropriate to competitive cyclists but are not appreciated by the main demographic groups targeted by e-bikes (i.e. commuters, leisure cyclists). Hence, in order to be as inclusive as possible the *ride to exhaustion* protocol has been excluded from this study.

Targeting the general population also imposes constraints on the selection of bicycle geometry setup that is comfortable for the participant, the time demanded by the test (e.g. $<$ 30 minutes) and the willingness to have physiological variables (e.g. hearth rate) measured via attaching sensors to the body (see Fig. 1).

According to Marsh and Martin [51], untrained cyclists at submaximal efforts (i.e. efforts that are typically limited between 10 to 20 minutes) exhibit unchanged Rated Perceived Exertion (RPE) [59] levels for loads of up to 150 W. That is to say that an effective and representative test protocol should include loads above such a value.

Based on this, the cadence to be sustained by participants during the test reported in this paper has been set to 80 $\pm$ 10 rpm (i.e. optimal cadence for endurance cycling [42]). Although an occasional male cyclist with a weight of 80 kg could struggle to sustain more than 200 W for periods of time $>$ 5 min [51], it is not uncommon for cyclists to encounter routes with > 5% gradients (i.e. the maximum recommended incline for cycle routes according to the UK Manual of the Streets [60]), which would demand, in no-wind condition, up to 300 W [30] to maintain an average speed of 20 km/h (i.e. average bicycle speed in urban area according to Strava®tracking service [61]) Thus to support the evaluation of performance at an even spread of loads both below and above the 200 W mark, the protocol was designed to include seven loads ranging from 42 W to 294 W in increments of 42 W. In order to maintain the duration of the test below 30 min, taking into account the time involved in the measurement and setup of bicycle geometry (between 8-10 minutes) and the warmup/cooldown period (i.e. 10-15 minutes recommended [62]) coupled with the reported endurance capabilities of the general public [51], the time at each load was set to 1 min.

Because cycling performance is affected by the bicycle geometry setup (i.e. the relative distances between the handlebar, saddle and bottom bracket. For example, an excessive distance between bottom bracket and saddle can lead to an ineffective torque production) [63] it was necessary to standardise the bicycle geometry for each participant. Although different techniques are available to determine the optimum geometry (e.g. video analysis [64], anthropometric measures [64]) a simple technique was adopted that consists of measurements for: (i) the knee angle when leg totally extended (foot at 6 o'clock position) to determine saddle height, (ii) the distance between the front of the knee and the pedal axle for the saddle setback, (iii) the angle between a horizontal line and the torso to determine handlebar height and (iv) the angle between the humerus and torso for the handlebar reach (see Table II for details on the magnitudes). This technique only requires the use of a goniometer [65] to measure the angles and a plumb line and takes typically 5 minutes to complete.

To minimise the invasiveness of the trial for the participants during data collection, heart rate and RPE were the only physiological variables/parameters measured during the test. Heart rate was measured with a frequency of 100Hz using a heart rate chest strap while RPE was recorded manually at each 30 second mark for each load with a scale ranging from 1 (i.e. easy, small effort) to 5 (i.e. maximum exertion). Fitness levels were recorded during the warmup and were self-assessed using a scale from 1 to 5, 1 being not active to 5 being an elite athlete. Cycling experience was determined based on the hours cycled per week (e.g. level 1 for less than 1 hour cycled per week, level 5 for more than 11 hours cycled per week). The test protocol, in terms of the features and recorded measurements, are detailed in Table I and Table II. Mechanical variables (i.e. torque and cadence) were recorded using a fully instrumented cycling ergometer developed at Loughborough University [66] that enables a 200Hz sampling frequency and the capability to control active mechanical resistance both in terms of torque and power.

TABLE I

TEST PROTOCOL SETUP

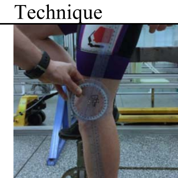
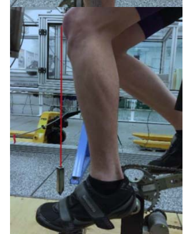
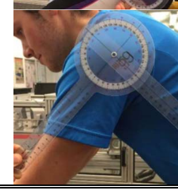
Parameter	Technique	Description
Saddle Height		Foot at 6 o'clock position, knee angle of 30°.
Saddle Setback		Foot at 3 o'clock position, front of knee aligned with pedal axle.
Handlebar Height		Angle between horizontal and shoulder joint of 45°.
Handlebar Reach		Angle between shoulder and elbow joints to be 90°.

TABLE II

TEST PROTOCOL PARAMETERS

Parameter	Magnitude
Initial Load	42 W
Load Increment	42 W / minute
Final Load	294 W
Cadence	80±10 rpm

C. Results

Fig. 2: Participants demographics information. shows the demographics of the participants. Out of the 30 participants only 5 (17%) were female.[1] constituted 40% of the participants suggesting possible interest in e-bikes for this group. *Competition*, *Fitness* and *Non-cycle* groups contributed with 33%, 10% and 17% respectively. The large majority of participants cycled on average between 2 (33%) to 3 (27%) hours per week which suggests that the distances they are likely travel are short (i.e. between 30-45 km in total), coinciding with the fact that viable cycling commuting distances fall within the 5 to 15 km range [10]. In terms of perceived fitness levels, most of the participants classed themselves as having an average fitness (43%). It is worth noting that although 10 participants were competition cyclists, only 40% of this category classed themselves as having the highest fitness level of 5.

In order to determine whether physiological factors had an impact of performance and techniques an analysis of variance (ANOVA) was applied to the dataset. In order to identify the most predominant factors a confidence of 95% (resulting in a p-value smaller and 0.05) was chosen as a threshold.

[1]Although not ideal this distribution is nevertheless representative of the fact that male are over three times more inclined to cycle than females [73] Commuters

TABLE III
TEST PROTOCOL DESCRIPTION: STORED VALUES

Feature	Description
Perceived Fitness Level	Scale 1 to 5 with 1 sedentary and 5 elite athletes
Cycling Experience	Scale 1 to 5 1→ < 1 h/week 2→ 1<x<3 h/week 3→ 3<x<7 h/week 4→ 7<x<11 h/week 5→ >11 h/week
Type of Cyclist	Occasional (Non-cycle) Fitness Commuting Competition
Effort Level (RPE)	Scale 1 to 5 1 easy, 5 maximum exertion
Heart Rate	Chest strap, $f_s = 100\ Hz$
Torque	Independent left and right measure at the crank, $f_s = 200\ Hz$
Cadence	$f_s = 200Hz$

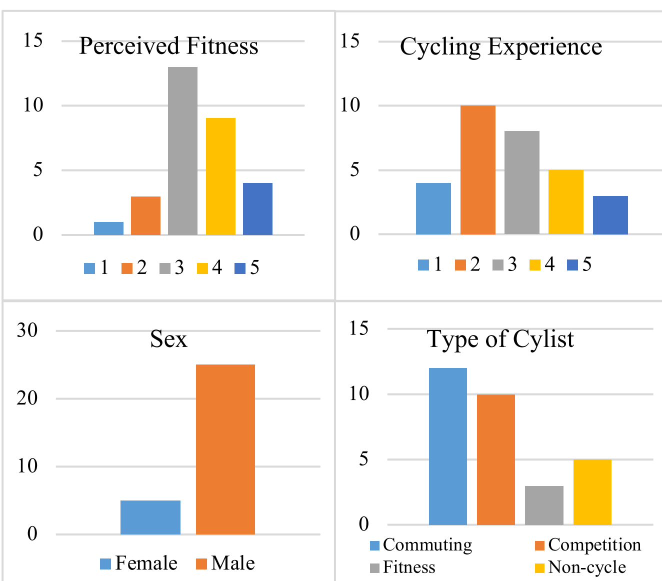


Fig. 2. Participants demographics information.

The rate of power application (i.e. how fast the power is delivered) resembles a general sinusoidal variation wave for all loads (see Fig. 3). The magnitude, the phase and location of the maximum/minimum outputs changes depending on the load (see Fig. 3). For example, between Load 1 and Load 7 the magnitude and phase differ by 3.4 W/° and ∠ 40° respectively. As the load increases, the maximum/minimum rate of power application occurs earlier in the cycling stroke. For example, the maximum value occurs at 70 ± 2.5° for Load 1 and at 50 ± 2.5° for Load 7. The same behaviour is observed for females.

1) Analysis by Sex: Even under controlled indoor/laboratory conditions, where the load can be kept constant, maintaining a constant output power is difficult [67]. To account for performance variability, Normalised Power (NP) (i.e. a parameter used to measure periods of intense effort during the overall workout) can be used as an estimate of the constant power that could have been maintained for the same physiological effort [68] [69]. As seen in Fig. 4, normalised power increases linearly with load (see III-C.2). Although this increase is slightly higher (2% difference between males and females) for males, there is no significant difference in the normalised power due to sex ($p > 0.05$).

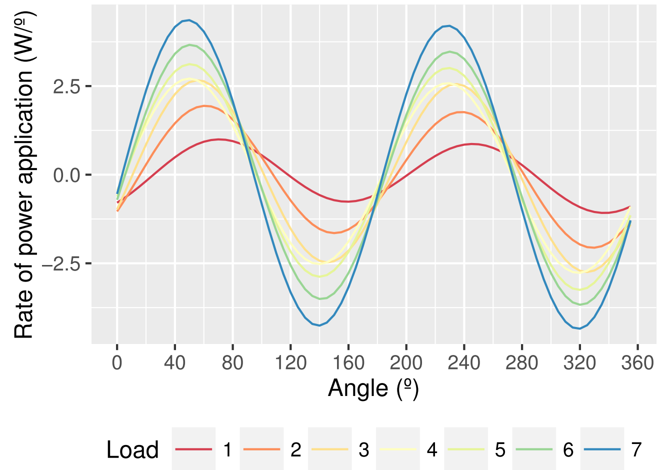


Fig. 3. Rate of power application per degree. Magnitude, phase and maximum/minimum occurrence vary with load.

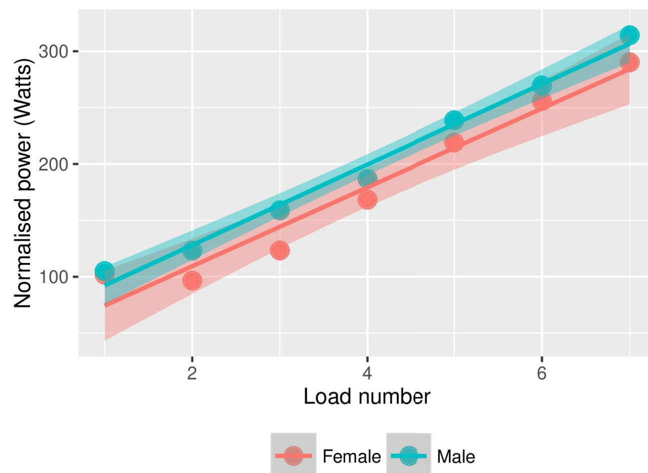


Fig. 4. Power test results by sex. No significant difference due to gender, linear increase on normalised power due to load. (Note: Bands indicate the uncertainties in the values).

TABLE IV
LINEAR FIT COEFFICIENTS FOR NORMALISED POWER PER SEX

Classifier	Intercept	Slope
Female	40.2	34.7
Male	56.7	35.7

2) Analysis by Cycling Background: For all cycling backgrounds (i.e. *Commuting*, *Competition*, *Fitness*, *Non-cycle*) the normalised power has a linear increase with the load. Up to Load 3 (126W) there is no significant difference

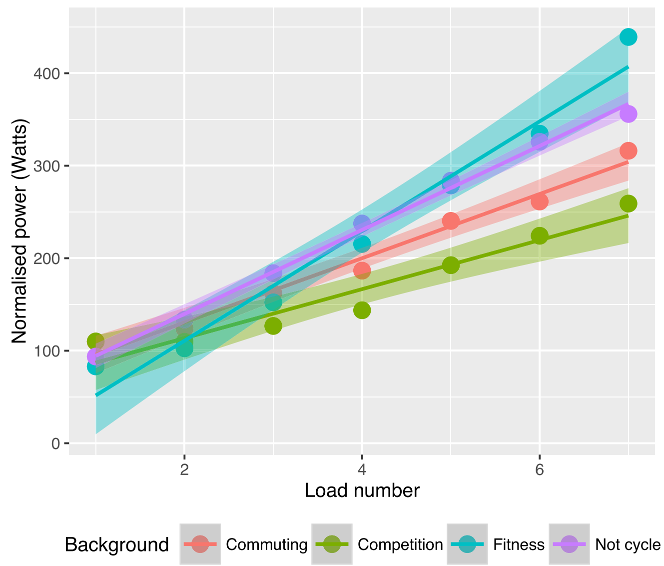


Fig. 5. Normalised power per background. Less experienced cyclists output larger normalised power for the same load.

TABLE V

LINEAR FIT COEFFICIENTS FOR NORMALISED POWER PER BACKGROUND

Classifier	Intercept	Slope
Commuting	61.7	34.5
Competition	60.6	27.0
Fitness	-4.0	57.9
Non-cycle	49.1	45.4

(i.e. 165 ± 25, 125 ± 20, 155 ± 25, 180 ± 10 W) in performance due to the cycling background (see Fig. 5), however above these loads the difference becomes significant ($p < 0.05$) between the lowest NP observed which occurs for *Competition* participants and other cycling background participants increases (i.e. 310 ± 20, 260 ± 30, 440 ± 45, 360 ± 13 W for *Commuting*, *Competition*, *Fitness*, *Non-cycle* at Load 7).

It is evident that more experienced participants output lower normalised power for the same load. For example, the difference between *Competition* and *Non-cycle* participants is close to 40±13% for Load 7. Based on the results observed for groups other than *Fitness*, it might be expected for the NP to be between the values observed for *Commuting* and *Non-cycle* however, this is not the case.

However, it is possible for the participants to have chosen a classification incompatible with their abilities [70]. Taking into account that there is no significant difference ($p > 0.05$) between the straight line fit for the *Non-cycle* and *Fitness* groups (see Fig. 5 and Table V), the NP output by less experienced cyclists is larger (i.e. 212 ± 13 W at Load 4 for *Commuting* and *Non-cycle*) for the same load than the one observed for experienced cyclists (i.e. 170 ± 30 W at Load 4 for *Competition*).

For larger loads (i.e. 5: 210 W, 6: 252 W, 7: 294 W; see Fig. 6), less experienced cyclists (i.e. *Commuting* and *Non-Cycle*) consistently produce higher maximum/minimum power values and sustain larger power values for longer segments during the pedal cycle. While *Competition* cyclists show a

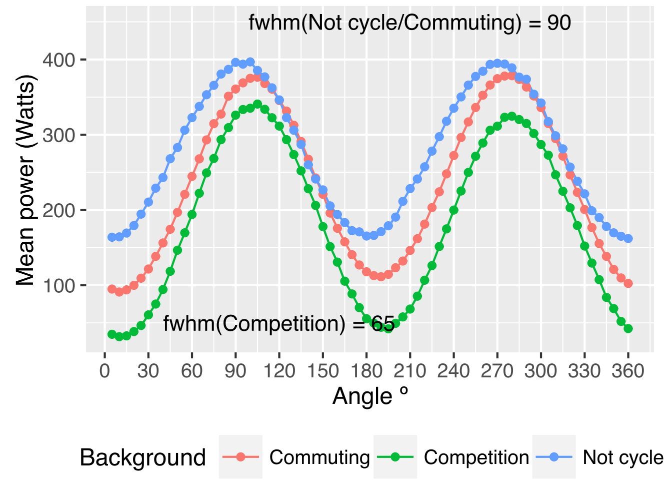


Fig. 6. Mean power per background for Load 7. Less experienced cyclists output larger power values across the pedal cycle.

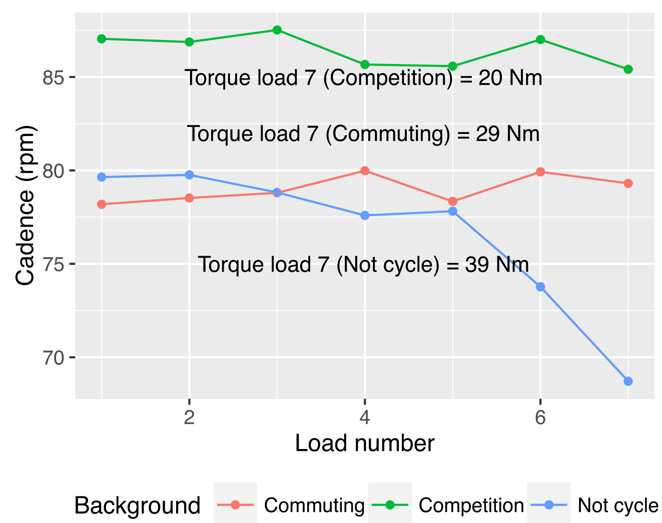


Fig. 7. Mean cadence per background. Less experienced cyclists favour lower cadences thus incurring in higher torques for the same load.

Full Width Half Maximum (FWHM) value of 65 ± 1°, other background type cyclists show a FWHM of 90 ± 5°. These findings would seem to be incompatible with the current belief that technique improves with experience and poses questions on the validity of cycling background as an accurate performance discriminant.

Fig. 7 shows the mean cadence that leads to the power difference observed in Fig. 5. While experienced cyclists maintain a higher cadence (at the upper limit of the experimental tolerance i.e. 86.4 ± 0.9 rpm throughout the test) thus requiring a lower torque at the cranks for similar power outputs, less experienced cyclists maintain lower (i.e. 78.9 ± 0.8 rpm for *Commuting*, 76.4 ± 4.2 rpm for *Non-cycle*) cadences (i.e. thus requiring in higher torques for the same load for equivalent power outputs).

The rate of power application (i.e. how fast the power is delivered) follows a sinusoidal pattern for all loads (see Fig. 3). Depending on the load the magnitude, phase and location of maximum/minimum occurrence changes (see Fig. 3).

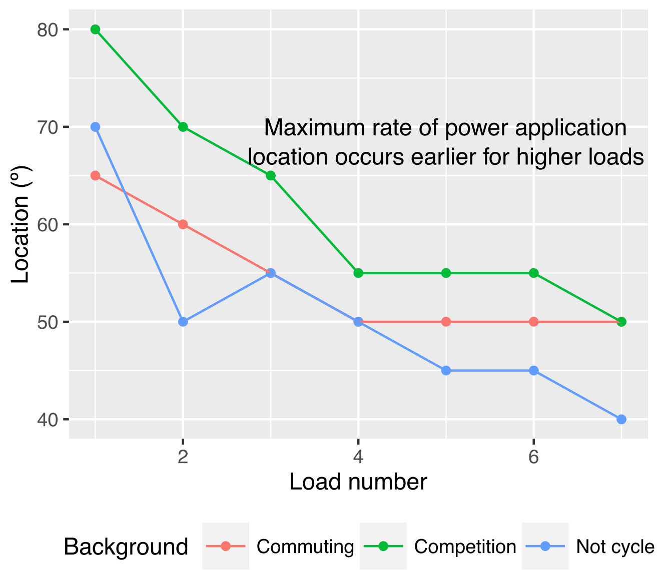


Fig. 8. Rate of power per background. Maximum rate of power application occurs earlier for higher loads.

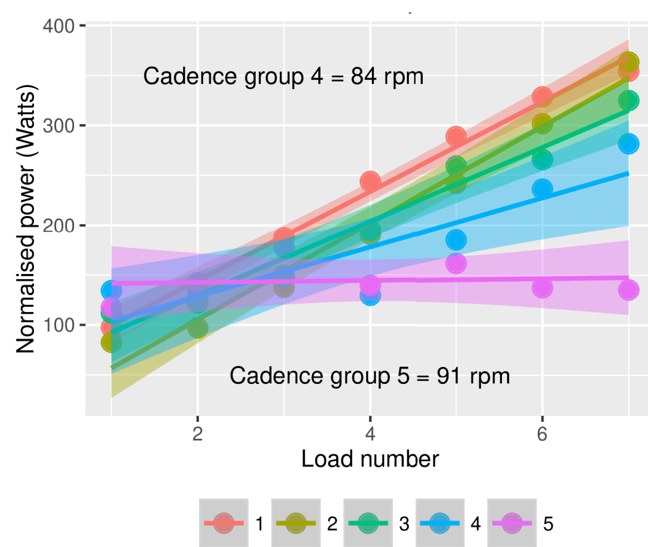


Fig. 9. Normalised power for hours per week. The rate of normalised power to load decreases with the increase of hours cycled per week.

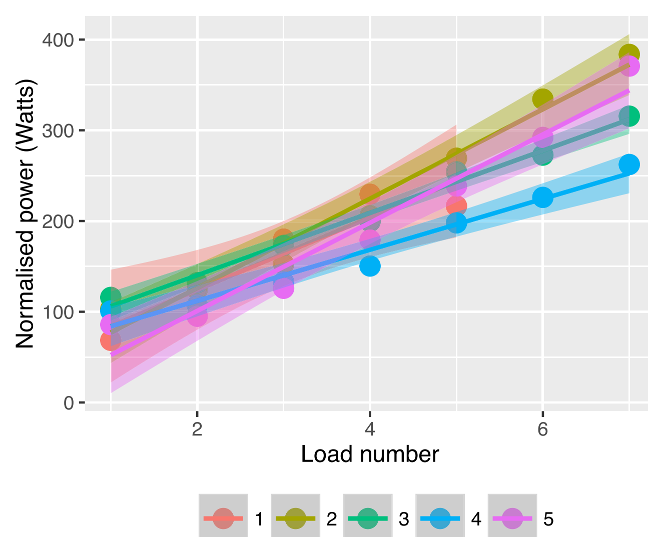


Fig. 10. Normalised power per fitness level. There is no clear difference for normalised power due to fitness level.

TABLE VI
LINEAR FIT COEFFICIENTS FOR NORMALISED POWER PER HOURS PER WEEK

Classifier	Intercept	Slope
1	57.0	40.0
2	8.4	50.0
3	56.0	37.0
4	79.0	24.7
5	140.3	1.05

The location of maximum/minimum rate of power application moves to an earlier location (Load 1: 71.7 ± 7.6°, Load 7: 46.7 ± 5.7°) across the pedal cycle as the load increases. As presented in Fig. 8 for less experienced cyclists the occurrence of the maximum rate of power application is earlier than for experienced cyclist (i.e. 45 ± 0.5° for *Non-cycle* compared with 55 ± 0.5° for *Competition* at 252W loads). However, it is noted that for Load 1 *Commuters* show the earliest rate of power application and for Loads 3 and 4 they have the same values as the Non-Cycle group (i.e. 55 ± 0.5°, 50 ± 0.5° respectively).

3) Analysis by Hours Cycled per Week: As the number of hours per week increases the change in NP with load decreases (see Fig. 9). For cyclists used to cycling more than 11 hours per week (i.e. Group 5) there is hardly any increase in normalised power due to the load (140.3 ± 40 W, see Table VI for the linear fit coefficients). From a total of 10 *Competition* cyclists, 3 are within Group 5, 3 are within Group 4 (i.e. between 7 and 11 hours per week) and 4 are within Group 3 (i.e. between 3 and 7 hours per week). The behaviour represented on Fig. 9 suggests that the *volume of hours ridden* has the most significant influence on performance when compared with the riders backgrounds since *Competition* cyclists have similar characteristics observed with cyclists with *Commuting* background (i.e. 1.81% difference in intercepts, $<$ 10° difference in slope in trendlines for the two groups) when they ride similar amount of hours per week. Fig. 9 also shows that the higher the hours cycled per week the lower is the slope of the linear fit for NP (i.e. linear-fit slope for group 1 is 40°, for group 5 is 1.05°). On the other hand, the mean cadence increases with the hours cycled per week (i.e. for group 4 the mean cadence was 84 ± 5 rpm whereas for group 5 the mean cadence was 91 ± 3 rpm).

4) Analysis by Perceived Fitness Level Fitness: level may not be a good discriminator of differences in performance as it is a subjective and self-assessed measure [70]. For example, some (n = 4) *Competition* participants classed themselves as having a perceived fitness level of 4. In fact, the results indicate that there is no significant difference for NP due to fitness level (less than 11° difference in linear-fit slope and less than 67W in intercept; see Fig. 10 and Table VII). Furthermore, since fitness level is not a direct indicator of cycling experience, the hours cycled per week represents the

TABLE VII
LINEAR FIT COEFFICIENTS FOR NORMALISED POWER PER FITNESS LEVEL

Classifier	Intercept	Slope
1	44.0	22.8
2	28.0	27.4
3	70.7	19.8
4	54.7	16.4
5	4.0	27.1

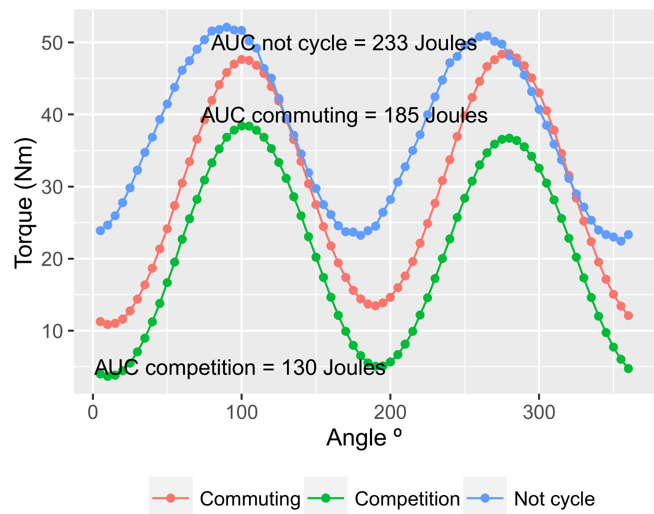


Fig. 11. Torque per cycling background.

best discriminator of improved performance from the results observed in this research.

D. Influence on Controller Operation

There are three main characteristics that can be observed in the test results, which are considered vital inputs for the controller operation i.e.: (i) the variation of rate of power application across the pedal cycle (see Fig. 3), (ii) the sinusoidal type behaviour of the mean power (see Fig. 6) and (iii) its associated torque (see Fig. 11).

As shown in Fig. 11 the torque applied during the pedal stroke varies sinusoidally with the angular position. This implies that the mechanical work (obtained by integrating torque with respect to angle of the crank arm [71], in Fig. 11 indicated as Area Under the Curve, AUC) obtained from the sinusoid will always be lower than the mechanical work for a constant torque value with magnitude larger or equal than the mean torque across the whole pedal cycle. It is hence more effective to guarantee that the net torque (i.e. the torque resulting from the contribution of both the cyclist and the e-bike's motor) is constant throughout the pedal cycle rather than to focus the controller on increasing its peak value. Implementing this kind of varying motor torque contribution is complicated by the fact that the magnitude of the contribution has to change depending on the angular position during the pedal cycle. For example, for the results shown in Fig. 11 if a constant torque of magnitude equal to the maximum torque is guaranteed by the controller, the increase in mechanical work

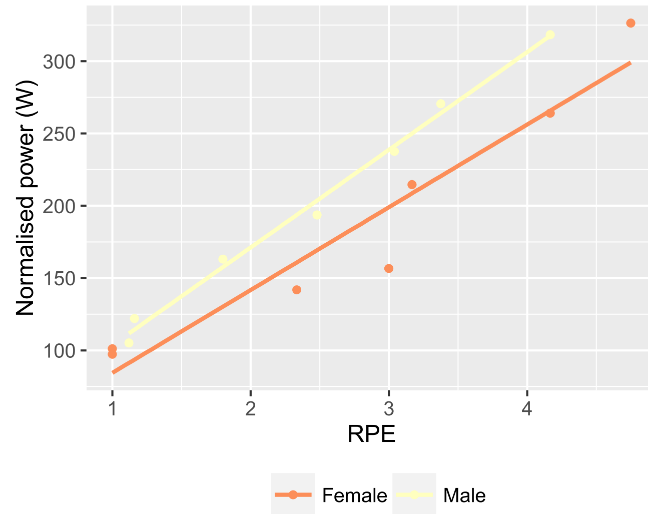


Fig. 12. Normalised Power Fit per Sex.

input to the e-bike system would be 64%, 85% and 41% for the *commuting*, *competition* and *non-cycle* groups respectively.

IV. PROPOSED CONTROLLER STRATEGIES

A. Fixed Percentage

The *fixed percentage* strategy is similar to the current *fixed gain* strategies [24]–[28] but differs significantly on how the percentage values are selected.

The controller strategy outlined in this paper uses the desired level of RPE and the desired level of assistance, both set by the user, based upon the results shown in Fig. 12. Under this strategy if the controller is set to have 5 levels of assistance, the percentages can be fixed as 20% for level 1 up to 100% for level 5 with 20% increments for the levels in between. If a female cyclist wished to keep an RPE level of 3 that would require a net NP input of 200W. Hence if she chooses an assistance level of 3 then she would only have to input 80W as the motor would contribute with the remaining 120W.

This approach differs from current controllers in that its contribution is based on the normalised power required to keep a set RPE level rather than adding a fixed gain factor to the average torque contribution delivered by the cyclist. If the cyclist inputs the complete 200 W required for an RPE level of 3 an assistance of level 3 would still contribute an extra 120 W accelerating the bicycle.

It is important to note that, for a successful implementation of this strategy, it is crucial to obtain an accurate model of RPE and determine how these trends are influenced not only by factors as sex, but also by experience (hours cycled per week). Further work should focus on studying how fatigue relates to physiological factors but also how can RPE be derived from quantitative measures.

B. Torque Filling

Torque filling control strategies are based on the mechanical work concept discussed in section III-D. Instead of focusing

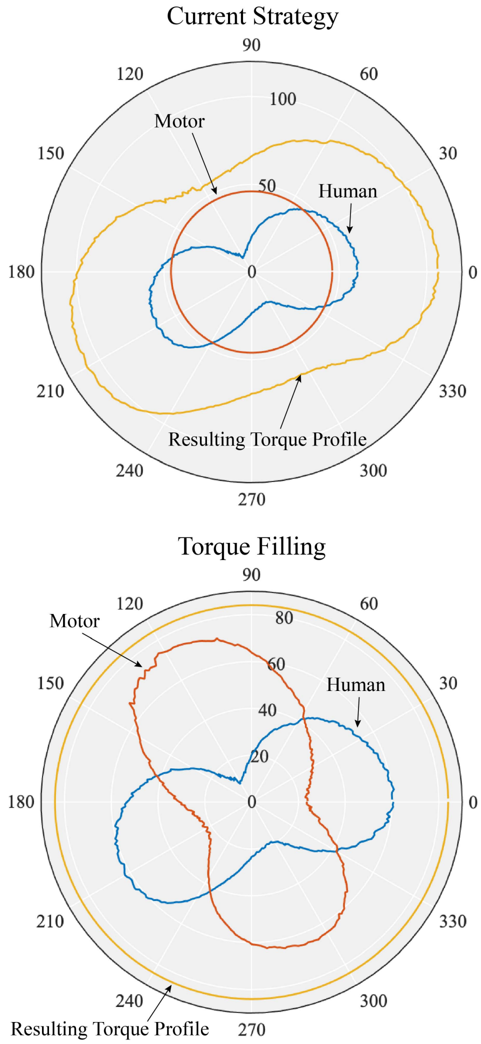


Fig. 13. *Torque Filling strategy* as it compares with the current strategy represented in Torque (Nm) vs Angle (°) plots. In the top figure, the current strategy (*Fixed Gain*) as it operates at a typical setting (120%) tends to accentuate humans' natural unbalances; it the bottom figure, the proposed (*Torque Filling*) strategy delivers a smooth torque profile whilst achieving identical mechanical work.

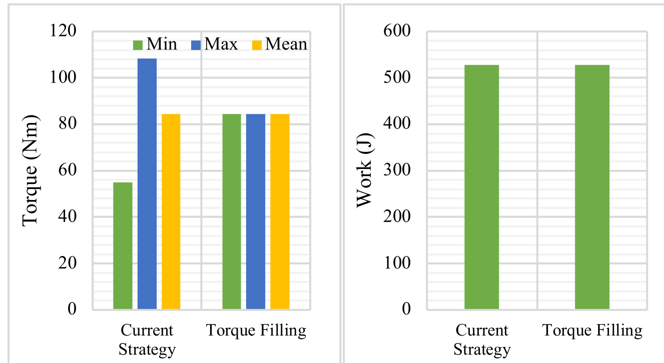


Fig. 14. Performance analysis of current strategy (*Fixed Gain*, 120%) against *Torque Filling*, the resulting torque profile shows smoothness without accentuating human natural imbalances. This is achieved without alerting the mechanical work of the motor resulting in a performance factor of 1.

on increasing the torque value, the controller is focused on ensuring that the torque is constant across the whole pedal cycle.

Determining, in real time, the appropriate value for the torque to be contributed by the motor requires more complex *feedforward* control algorithms which would have to take into account the fact that the required action would occur when the location across the pedal cycle has already changed [50]. Additional controller logic is also required to prevent unwanted input from the motor if the cyclist wishes to coast without pedalling or if the cyclist is slowing down. Without such logic the controller would interpret the input as of 0 W thus contributing with a large but unwanted input to the system torque. Either a cadence threshold or a mechanical input trigger could be used to accommodate this functionality.

This technique differs from the current commercial solutions by the fact that the fixed gain strategy will result in enhancing the torque fluctuations that a human naturally produce around the crank arm for the very nature of the cycling activity. Additionally, torque filling will try to compensate for human inefficiencies by providing maximum torque at the locations where the human output is reduced, resulting in a smooth power delivery throughout the entire crank revolution.

C. Real-Time Power Mapping

Two different power mapping approaches can be based on fitting linear relationships between the normalised power and the variables measured during the testing protocol (e.g. torque, cadence, heart rate).

Fig. 12 shows that the linear relationships can be derived between the NP and the RPE level which changes depending on whether if the cyclists are either male or female. Using these relationships, the controller can determine how much power the motor needs to contribute based on the measured power input by the cyclists. For example, for a male cyclist desiring an RPE level of 3 a net normalised power 230W is required. Therefore, if the cyclist inputs 100W the motor must contribute 130W. If the rider increased its input to 200 W the motor contribution would be reduced to 30 W. The linear relationship can be extended to include the different classifications used within the experimental trials discussed in this paper (i.e. Sex, cycling experience, Hours cycled per week, Perceived fitness). Because the motor contribution varies according to the user input there is no need to measure the changes caused by variations in the environmental conditions (e.g. wind resistance, incline) as they would be indirectly accommodated via the increase in the cyclist's power input.

This type of power mapping can also be used to set a maximum power limit which the cyclist can sustain for a particular RPE level. For example, if the maximum normalised power for an RPE level of 3 is 230W but the required power to move at a desired speed under current environmental conditions (e.g. wind resistance, incline) is above 230 W then the controller needs to ensure that the motor can contribute the difference. Using the controller in this way would require environmental changes to be monitored but would guarantee a constant RPE level for the duration of the ride.

V. Conclusions and Future Work

The current state-of-the-art electric bicycles are hybrid lightweight vehicles that attempt to assist humans in generating mechanical power with the aid of a brushless DC (BLDC) motor. The large majority of electric bicycles available of the marked in Europe and North America seem to have adopted a common approach to control the level of assistance provided by the motor throughout a ride i.e. a fixed gain strategy requires the rider to select between three to five levels of assistance, the motor then measures the torque generated by cyclist and provides a torque proportional to that input in accord with the selected gain. However, there is no attention to physiological factors of the rider (i.e. sex, experience, RPE) and the current assistance tends to accentuate the natural inabilities of cyclists to deliver a smooth torque across the pedal stroke, resulting in fluctuations and inefficiencies.

In this paper, an incremental sub-maximal ramp test has been detailed to study pedalling characteristics and how they relate to physiological factors of participants. Thirty volunteers took part in this study, the data analysis enabled the identification of factors that provided statistical differences with respect to common performance factors such as mechanical power and normalised power. Sex, cycling experience and cycling background were the most valid discriminants.

Using the findings of this study three novel controller strategies have been proposed. They show how improved awareness of the human conditions and capabilities can result in a better accommodating symbiosis between human and machine to deliver a new generation e-bike.

Fixed percentage is a simple improvement of the current state-of-the-art fixed gain strategy, as it offers the inclusion of physiological factors such rate of perceived exertion (RPE), it is easy to implement and does not require extra computation. *Torque Filling* offers options for a smoother power delivery with the possibility to compensate human imbalances and efficiencies, it requires torque sensors already present in most commercial electric bicycles and a controller to compute the new torque profile at each pedal revolution. Finally, *Real-Time Power mapping* offers a more comprehensive inclusion of physiological factors in the controller strategy by mapping factors such as cycling experience, technical preparation and perceived level of fitness however, it requires a more comprehensive study of the riders' capability, possibly including a continuous adaptation approach; this requires a complex system including the backend support of cloud computing to store users' profiles.

Further analysis is necessary to assess the complex relationship between cyclist and bicycle with particular attention to factors such as technique and fatigue. Further factors can be analysed such as Functional Threshold Power (FTP), Intensity Factor (IF) and Training Stress Score (TSS). The RPE could benefit of the use of a more commonly adopted scale such as the one proposed by Borg. Moreover, a physical implementation of the strategies proposed needs to be validated against the expected outcome. Some of the strategies proposed require convoluted controllers and their hardware implementation could be challenging for an embedded system.

Finally, the sample size for this study resulted to be not equally representative of both sexes. Further iterations of these research should include a larger sample size, possibly including an equal number of male and female participants.

References

[1] A. E. van den Berg, T. Hartig, and H. Staats, "Preference for nature in urbanized societies: Stress, restoration, and the pursuit of sustainability," *J. Social Issues*, vol. 63, no. 1, pp. 79–96, Mar. 2007.

[2] A. Haveman-Nies, "Dietary quality, lifestyle factors and healthy ageing in europe: The SENECA study," *Age Ageing*, vol. 32, no. 4, pp. 427–434, Jul. 2003.

[3] *Diesel Engine Exhaust Carcinogenic*, World Health Org., Int. Agency Res. Cancer, Lyon, France, 2012.

[4] T. Goldman and R. Gorham, "Sustainable urban transport: Four innovative directions," *Technol. Soc.*, vol. 28, nos. 1–2, pp. 261–273, Jan. 2006.

[5] J. Weinert, C. Ma, and C. Cherry, "The transition to electric bikes in China: History and key reasons for rapid growth," *Transportation*, vol. 34, no. 3, pp. 301–318, May 2007.

[6] K. Sangani, "E-bikes take off," *Eng. Technol.*, vol. 4, no. 10, pp. 34–35, Jun. 2009.

[7] E. Fishman and C. Cherry, "E-bikes in the mainstream: Reviewing a Decade of Research," *Transp. Rev.*, vol. 36, pp. 1–20, Jul. 2016.

[8] Q. Perrot, *The Emergence of Electric Bikes in China*. Stanford, CA, USA: Stanford Univ., 2015.

[9] Y. Ruan, C. C. Hang, Y. M. Wang, and R. F. Ma, "The role of government in an emerging disruptive innovation: The case of E-bike in China," in *Proc. IEEE Int. Conf. Manage. Innov. Technol. (ICMIT)*, Sanur Bali, Indonesia, Jun. 2012.

[10] W. C. Morchin and H. Oman, *Electric Bicycles: A Guide to Design and Use* (Electric Bicycle Manual), vol. 8. Hoboken, NJ, USA: Wiley, 2006.

[11] D. L. Gadenne, J. Kennedy, and C. McKeiver, "An empirical study of environmental awareness and practices in SMEs," *J. Bus. Ethics*, vol. 84, no. 1, pp. 45–63, Jan. 2009.

[12] J. Cappelle, J.-M. Timmermans, P. Lataire, G. Maggetto, and P. Van Den Bossche, "Electrically assisted cycling around the world," in *Proc. 20th Int. Electr. Vehicle Symp.*, 2003, pp. 1–12.

[13] A. Muetze and Y. Tan, "Electric bicycles—A performance evaluation," *IEEE Ind. Appl. Mag.*, vol. 13, no. 4, pp. 12–21, Jul. 2007.

[14] E. Starschich and A. Muetze, "Comparison of the performances of different geared brushless-DC motor drives for electric bicycles," in *Proc. IEEE Int. Electr. Mach. Drives Conf.*, Antalya, Turkey, May 2007, pp. 140–147.

[15] P.-H. Chen, "Application of fuzzy intelligence to Elebike control design," in *Proc. 6th Int. Fuzzy Syst. Conf.*, Barcelona, Spain, 1997, pp. 199–206.

[16] C.-Y. Liang, W.-H. Lin, and B. Chang, "Applying fuzzy logic control to an electric bicycle," in *Proc. 1st Int. Conf. Innov. Comput., Inf. Control (ICICIC)*, vol. 1, Beijing, China, 2006, pp. 513–516.

[17] M. Watsford, M. Ditroilo, E. FernáNdez-PeñA, G. D'Amen, and F. Lucertini, "Muscle stiffness and rate of torque development during sprint cycling," *Med. Sci. Sports Exerc.*, vol. 42, no. 7, pp. 1324–1332, Jul. 2010.

[18] E. Coyle *et al.*, "Physiological and biomechanical factors associated with elite endurance cycling performance," *Med. Sci. Sports Exercise*, vol. 23, no. 1, pp. 93–107, 1991.

[19] P. Giani, M. Corno, M. Tanelli, and S. M. Savaresi, "Cyclist heart rate control via a continuously varying transmission," *IFAC Proc. Volumes*, vol. 47, no. 3, pp. 912–917, 2014.

[20] J. A. Afonso, F. J. Rodrigues, D. D. R. Pedrosa, and J. L. Afonso, "Automatic control of cycling effort using electric bicycles and mobile devices," in *Proc. World Congr. Eng. (WCE)*, vol. 1. London, U.K.: IAENG, Jul. 2015.

[21] M. Corno, P. Giani, M. Tanelli, and S. M. Savaresi, "Human-in-the-loop bicycle control via active heart rate regulation," *IEEE Trans. Control Syst. Technol.*, vol. 23, no. 3, pp. 1029–1040, May 2015.

[22] B. Xhyheri, O. Manfrini, M. Mazzolini, C. Pizzi, and R. Bugiardini, "Heart Rate Variability Today," *Prog. Cardiovascular Diseases*, vol. 55, no. 3, pp. 321–331, 2012.

[23] R. Krishnan, *Electric Motor Drives: Modeling, Analysis, and Control*. Upper Saddle River, NJ, USA: Prentice-Hall, 2001.

[24] Robert Bosch GmbH. (2017). *Bosch eBike Systems*. Accessed: Jul. 2017. [Online]. Available: https://www.bosch-ebike.com/en/

[25] Brose Antriebstechnik GmbH & Co. (2017). *Brose Antriebstechnik*. Accessed: Jul. 2017. [Online]. Available: http://www.brose-ebike.com/en/

[26] Yamaha Motor Co. (2017). *e-Bike Systems*. Accessed: Jul. 2017. [Online]. Available: https://global.yamaha-motor.com/business/e-bike-systems/index.html

[27] Panasonic Industry Europe GmbH 2018. Panasonic Industry Europe. (2018). *E-Bike Systems*. Accessed: 2018. [Online]. Available: https://eu.industrial.panasonic.com/products/e-bike-systems

[28] Shimano. (2017). *Shimano STEPS e-bikes*. Accessed: Jul. 2017. [Online]. Available: https://www.shimano-steps.com/e-bikes/united-kingdom/en

[29] R. Hatano, D. Namikawa, R. Minagawa, and M. Iwase, "Experimental verification of effectiveness on driving force assist control based on repetitive control for electrically-assisted bicycles," in *Proc. IEEE 13th Int. Workshop Adv. Motion Control (AMC)*, Yokohama, Japan, Mar. 2014, pp. 237–241.

[30] P. E. di Prampero, G. Cortili, P. Mognoni, and F. Saibene, "Equation of motion of a cyclist," *J. Appl. Physiol.*, vol. 47, no. 1, pp. 201–206, Jul. 1979.

[31] S. Mammar, N. A. Oufroukh, and S. Glaser, "Reducing rider effort for electric bicycles by environment disturbance compensation," in *Proc. IEEE Int. Conf. Control Appl. (CCA)*, Denver, CO, USA, Sep. 2011, pp. 550–555.

[32] H. Yabushita, Y. Hirata, K. Kosuge, and Z. Wang, "Environment-adaptive control algorithm of power assisted cycle," in *Proc. 29th Annu. Conf. IEEE Ind. Electron. Soc. (IECON)*, Roanoke, VA, USA, Nov. 2003, pp. 1962–1967.

[33] K. Hatada and K. Hirata, "Power assisting control for electric bicycles using an adaptive filter," in *Proc. IEEE Int. Conf. Ind. Technol. (ICIT)*, Busan, South Korea, Feb. 2014, pp. 51–54.

[34] S. Glueck, M. Pausch, and F. Benkert, "Bottom bracket with a torque sensor unit," U.S. Patent 8 797 027 B2, Dec. 21, 2007.

[35] H. Takebayashi, "Bicycle control system," U.S. Patent 20 090 088 934 A1, Sep. 28, 2007.

[36] S. Indulal and P. S. C. Nair, "A novel approach in automatic control of a hybrid bicycle," in *Proc. IET-UK Int. Conf. Inf. Commun. Technol. Electr. Sci. (ICTES)*, Tamilnadu, India, 2007, pp. 296–301.

[37] *European Parliament and of the Council of 15 January 2013 on the Approval and Market Surveillance of Two- or Three-Wheel Vehicles and Quadricycles Text With EEA Relevance*, document (EU) No 168/2013, European Parliament, Council of the European Union, Jan. 2013. Accessed: Aug. 10, 2019. [Online]. Available: http://data.europa.eu/eli/reg/2013/168/oj

[38] S. Mohammad, T. M. Guerra, J. M. Grobois, and B. Hecquet, "Heart rate control during cycling exercise using Takagi-Sugeno models," *IFAC Proc. Volumes*, vol. 44, no. 1, pp. 12783–12788, Jan. 2011.

[39] U. R. Acharya, K. P. Joseph, N. Kannathal, L. C. Min, and J. S. Suri, "Heart rate variability: A review," *Med. Biol. Eng. Comput.*, vol. 44, pp. 1031–1051, Nov. 2006.

[40] T. Nagata, S. Okada, and M. Makikawa, "Electric motor assisted bicycle as an aerobic exercise machine," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, San Diego, CA, USA, Aug. 2012, pp. 1933–1935.

[41] F. Özyener, H. B. Rossiter, S. A. Ward, and B. J. Whipp, "Influence of exercise intensity on the on- and off-transient kinetics of pulmonary oxygen uptake in humans," *J. Physiol.*, vol. 533, no. 3, pp. 891–902, Jun. 2001.

[42] C. R. Abbiss, J. J. Peiffer, and P. Laursen, "Optimal cadence selection during cycling," *Int. SportMed. J.*, vol. 10, no. 1, pp. 1–15, 2009.

[43] Y. Takada, H. Miyazawa, A. Uetake, K. Tanaka, H. Nakazato, and K. Shinkai, "Sensor, drive force auxiliary device using the sensor, and torque sensor zero point adjusting mechanism of the drive force auxiliary device," U.S. Patent 6 163 148 A, Oct. 16, 1996.

[44] P. Spagnol, M. Corno, R. Mura, and S. M. Savaresi, "Self-sustaining strategy for a hybrid electric bike," in *Proc. Amer. Control Conf.*, Washington, DC, USA, Jun. 2013, pp. 3479–3484.

[45] V. V. Haerri, M. Lindegger, and M. Neumaier, "A novel interior permanent synchronous motor for a high end ebike drive chain," in *Proc. 5th Int. Electr. Drives Prod. Conf. (EDPC)*, Nuremberg, Germany, Sep. 2015, pp. 1–6.

[46] W. Chlebosz, G. Ombach, and J. Junak, "Comparison of permanent magnet brushless motor with outer and inner rotor used in e-bike," in *Proc. 19th Int. Conf. Electr. Mach. (ICEM)*, Rome, Italy, Sep. 2010, pp. 1–5.

[47] T. P. Gavin, J. B. Van Meter, P. M. Brophy, G. S. Dubis, K. N. Potts, and R. C. Hickner, "Comparison of a field-based test to estimate functional threshold power and power output at lactate threshold," *J. Strength Conditioning Res.*, vol. 26, no. 2, pp. 416–421, Feb. 2012.

[48] J. Denham, J. Scott-Hamilton, A. D. Hagstrom, and A. J. Gray, "Cycling power outputs predict functional threshold power and maximum oxygen uptake," *J. Strength Conditioning Res.*, Sep. 2017, doi: 10.1519/jsc.0000000000002253.

[49] M. C. Miller, G. L. Moir, and S. R. Stannard, "Validity of using functional threshold power and intermittent power to predict cross-country mountain bike race outcome," *J. Sci. Cycling*, vol. 3, no. 1, pp. 16–20, 2014.

[50] W. Bertucci, F. Grappe, A. Girard, A. Betik, and J. D. Rouillon, "Effects on the crank torque profile when changing pedalling cadence in level ground and uphill road cycling," *J. Biomechanics*, vol. 38, no. 5, pp. 1003–1010, May 2005.

[51] A. P. Marsh and P. E. Martin, "Perceived exertion and the preferred cycling cadence," *Med. Sci. Sports Exerc.*, vol. 30, no. 6, pp. 942–948, Jun. 1998.

[52] A. Lucia *et al.*, "In professional road cyclists, low pedaling cadences are less efficient," *Med. Sci. Sports Exerc.*, vol. 36, no. 6, pp. 1048–1054, Jun. 2004.

[53] R. R. Bini, P. A. Hume, F. J. Lanferdini, and M. A. Vaz, "Effects of body positions on the saddle on pedalling technique for cyclists and triathletes," *Eur. J. Sport Sci.*, vol. 14, no. 1, pp. 1391–1746, 2014.

[54] E. A. Hansen, B. R. Rønnestad, G. Vegge, and T. Raastad, "Cyclists' improvement of pedaling efficacy and performance after heavy strength training," *Int. J. Sports Physiol. Perform.*, vol. 7, no. 4, pp. 313–321, Dec. 2012.

[55] S. L. Halson, "Monitoring training load to understand fatigue in athletes," *Sports Med.*, vol. 44, no. S2, pp. 139–147, Nov. 2014.

[56] K. Currell and A. E. Jeukendrup, "Validity, reliability and sensitivity of measures of sporting performance," *Sports Med.*, vol. 38, no. 4, pp. 297–316, 2008.

[57] D. E. R. Warburton, M. J. F. Haykowsky, H. A. Quinney, D. P. Humen, and K. K. Teo, "Reliability and validity of measures of cardiac output during incremental to maximal aerobic exercise," *Sports Med.*, vol. 27, no. 1, pp. 23–41, 1999.

[58] D. J. Sanderson and A. Black, "The effect of prolonged cycling on pedal forces," *J. Sports Sci.*, vol. 21, no. 3, pp. 191–199, Jan. 2003.

[59] G. Borg, *Borg's Perceived Exertion And Pain Scales*. Champaign, IL, USA: Human Kinetics, 1998.

[60] G. Merron, B. Andrews, and T. Dunwoody, *Manual for Streets*. London, U.K.: Department for Transport, 2007.

[61] Strava, Inc. (2018). *Strava*. Accessed: Nov. 1, 2018. [Online]. Available: https://www.strava.com

[62] M. Burnley, J. H. Doust, and A. M. Jones, "Effects of prior warm-up regime on severe-intensity cycling performance," *Med. Sci. Sports Exerc.*, vol. 37, no. 5, pp. 838–845, May 2005.

[63] A. R. Chapman, B. Vicenzino, P. Blanch, J. J. Knox, S. Dowlan, and P. W. Hodges, "The influence of body position on leg kinematics and muscle recruitment during cycling," *J. Sci. Med. Sport*, vol. 11, no. 6, pp. 519–526, Nov. 2008.

[64] V. Ferrer-Roca, A. Roig, P. Galilea, and J. García-López, "Influence of saddle height on lower limb kinematics in well-trained cyclists: Static Vs. Dynamic evaluation in bike fitting," *J. Strength Conditioning Res.*, vol. 26, no. 11, pp. 3025–3029, Nov. 2012.

[65] J. M. Rothstein, P. J. Miller, and R. F. Roettger, "Goniometric Reliability in a Clinical Setting: Elbow and Knee Measurements," *Phys. Therapy*, vol. 63, no. 10, pp. 1611–1615, 1983.

[66] N. Chakravorti, H. Lugo, L. K. Philpott, P. P. Conway, and A. A. West, "Automated cycling ergometer with built-in ability to produce resistance profiles," in *Proc. IEEE Int. Conf. Syst., Man, Cybern. (SMC)*, San Diego, CA, USA, Oct. 2014, pp. 2977–2982.

[67] M. Garcin, J.-F. Vautier, H. Vandewalle, M. Wolff, and H. Monod, "Ratings of perceived exertion (RPE) during cycling exercises at constant power output," *Ergonomics*, vol. 41, no. 10, pp. 1500–1509, Oct. 1998.

[68] H. Allen and A. Coggan, *Training and Racing With a Power Meter*. Boulder, CO, USA: VeloPress, 2010.

[69] A. Coggan. TrainingPeaks, LLC. (Feb. 10, 2016). *Normalized Power, Intensity Factor and Training Stress Score*. Accessed: Oct. 10, 2018. [Online]. Available: https://www.trainingpeaks.com/blog/normalized-power-intensity-factor-training-stress/

[70] J. F. Sallis and B. E. Saelens, "Assessment of physical activity by self-report: Status, limitations, and future directions," *Res. Quart. Exercise Sport*, vol. 71, no. 2, pp. 1–14, Jun. 2000.

[71] J. M. Rothstein, A. Delitto, D. R. Sinacore, and S. J. Rose, "Electromyographic, peak torque, and power relationships during isokinetic movement," *Phys. Therapy*, vol. 63, no. 6, pp. 926–933, Jun. 1983.

[72] J. Lindsey. Bicycling. (Jul. 14, 2013). *Guide to Power Meter Metrics*. Accessed: Oct. 10, 2018. [Online]. Available: http://www.bicycling.com/training/fitness/guide-power-meter-metrics

[73] Cotterell. CTC. (Feb. 15, 2018). *Cycling UK's Cycling Statistics*. Accessed: Oct. 10, 2018. [Online]. Available: https://www.cyclinguk.org/resources/cycling-uk-cycling-statistics#Do%20men%20cycle%20more%20than%20women?

[74] L. A. Shepard, "The centrality of test use and consequences for test validity," *Educ. Meas. Issues Pract.*, vol. 16, no. 2, pp. 5–24, Oct. 2005.

Lorenzo Stilo was born in Rome, Italy, in 1989. He received the B.Sc. degree in electronics engineering from the University of Rome Tor Vergata, Rome, in 2015, and the M.Sc. degree (Hons.) in embedded systems from Heriot-Watt University, Edinburgh, Scotland, in 2016. He is currently pursuing the Ph.D. degree in embedded intelligence with Loughborough University, Loughborough, U.K.

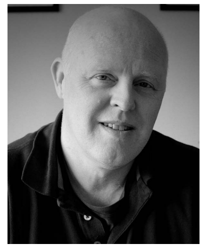
In 2015, he had a brief working experience as a Software Engineer with the Test Engineering Department within Defence Industry at Capgemini Italia S.p.A. and Elettronica SpA. He is a full-time Postgraduate Researcher with the EPSRC Centre for Doctoral Training in Embedded Intelligence. He is also a part of the Embedded Integrated Intelligent Systems Group, Loughborough University. His research interests include electric vehicles, personalisation in manufacturing, and human–machine interaction.

Heinz Lugo received the B.Sc. and M.Sc. degrees in mechanical engineering from the University of Los Andes, Bogota, Colombia, in 2009, and the Ph.D. degree in system engineering from Loughborough University, Loughborough, U.K., in 2008.

From 2013 to 2018, he was a Research Associate with the Embedded Integrated Intelligent Systems Group, Loughborough University, focusing on design and implementation of data analytics and machine learning tools for the sports and electronics manufacturing industries. He is currently working as a Senior Data Scientist with INCUS Performance Ltd. His research interests include data analytics, machine learning, and artificial intelligence.

Diana Segura Velandia received the bachelor's degree in chemical engineering from the University of Los Andes, Bogota, Colombia, and the Ph.D. degree in manufacturing from Loughborough University, U.K.

She has experience in applying artificial intelligence methods to solve problems in electronics manufacturing, healthcare, and automotive domains for monitoring, defect prediction, and design for manufacture and asset traceability and tracking. She is currently a Lecturer in ICT for manufacturing with the Department of Mechanical, Manufacturing and Electrical Engineering, Loughborough University. Her current research interests include artificial intelligence, decision making, materials, sensors, and modeling and simulation.



Paul P. Conway (Senior Member, IEEE) received the B.Eng. degree (Hons.) from the University of Ulster in 1988 and the M.Sc. degree from Loughborough University, Loughborough, U.K., in 1989.

He was an Industrial Engineer and a Research Assistant on a project addressing process modeling of reflow soldering with Fisher Body Overseas Corporation and General Motors Corporation. He is currently a Professor of manufacturing processes with Loughborough University and the Director of the Research Council's U.K. Innovative Electronics Manufacturing Research Centre (IeMRC). He has held a number of substantial Research Council, the European Framework Programme, and industrially funded research projects. He has published widely in the field of electronic manufacturing technology. He received the Institution of Production Engineers—Shorts Brothers PLC Prize for his B.Eng. degree.

Andrew A. West (Member, IEEE) is currently a Professor of intelligent systems with the Wolfson School of Mechanical, Electrical and Manufacturing Engineering, Loughborough University, Loughborough, U.K. He has over 25 years of experience in research and industrial consultancy with the University of Leeds, Leeds, U.K., the University of Cambridge, Cambridge, U.K., and Loughborough University. In addition, he is also the Managing Director of a university spinoff company involved in the development of next-generation healthcare systems and a Board Member of a U.S.-based sports product development and exploitation company. He is the author of over 170 journal and conference research publications. His collaborative research with the Engineering and Physical Sciences Research Council, the European Union, and the U.K. Technology Strategy Board has generated over $25 million income to Loughborough University. His main research interests include lifecycle engineering of intelligent distributed component-based manufacturing control and monitoring systems.

Prof. West was a recipient of 12 SMART Awards for local small- to medium-scale enterprises since 1999.