Chapter

The Impact of Virtual Environments for Future Electric Powered-Mobility Development Using Human-in-the-Loop: Part B - Virtual Testing and Physical Validation

Jun Jie Chong, Peter J. Kay, Daisuke Yashiro and Wei-Chin Chang

Abstract

Electric vehicles are increasing in popularity worldwide, and there have been numerous advances in technology to increase the energy efficiency of the vehicle and reduce the range anxiety for the user. For example, the latest electric vehicle (Tesla model S, equipped by 100kWh battery) available in the market in 2019 is able to drive around 375 miles. However, human behavior such as driving strategy is an important issue that impacts on energy optimization and ultimately vehicle range. Human behavior is rather complex and is difficult to replicate with computer algorithms. Therefore, to fully assess the impact of a particular technology, the interactions between humans, vehicle, and the environment need to be examined simultaneously, through a Human-in-the-Loop approach. In this chapter, the results of investigating a human-in-the-loop test platform, which incorporate human-driving behavior and the vehicle characteristics, are presented. In addition, this chapter analyzes a driving strategy, using a Human-in-the-Loop approach, applied to optimizing the energy usage for an electric vehicle competition.

Keywords: human-in-the-loop, driving simulator, energy consumption prediction, energy management optimization

1. Introduction

Increasing levels of simulation is being adopted throughout the Automotive engineering industry. In a driving simulator, unlike the real world, the environment can be strictly controlled. For example, the weather conditions, traffic and topography can all be controlled. In other words, it makes it easier to decouple the driver behavior from the other variables. In this context, the use of a simulator would reduce the time and cost of optimizing the driver strategy and examine the performance of the vehicle.

Kemeny and Panerai [1] have defined a driving simulator as a system that provides a coherent multi-sensory environment for a driver to perceive and control virtual vehicle movements. The use of driving simulators is becoming ubiquitous within the automotive sector. Driving simulators offer significant advantages over real world testing such as controllability/reproducibility, cost and ease of data collection [2].

Coupled with the increased use of driving simulators, the importance of model-based development (MBD) [3, 4] has increased. The automotive industry has proactively adopted MBD for product development [5]. However, there are only few professional engineers involved in automobile development having sufficient experience for performing MBD. To cultivate our next generation, there are some competitions (e.g. Formula Students, Shell Eco Marathon, Ene-1 GP SUZUKA competition, etc.) designed for institutions that reinforce the MBD technique.

The automotive industry is currently undergoing a technical revolution, in the face of climate change, and is moving away from conventional ICE vehicles to full-electric vehicles.

However, there are well established challenges with transitioning to full electric vehicles, namely the speed/range trade-off due to the limited capacity of current battery technologies [6]. The higher the mean speed, the shorter the range and vice versa. The Ene-1 GP SUZUKA competition is a competition that encapsulates the challenges faced by this transition to full electric vehicles. The aim of the competition is to design and manufacture a full electric car that will complete three laps of the Suzuka F1 circuit in the quickest possible time. Therefore, much effort is spent by the competitors to determine the optimum driving strategy to minimize the limited electrical energy available. Development of these strategies will also be applicable to commercial electric vehicles.

As mentioned in the previous chapter, the virtual environment is gaining attention in automotive industry. The model is integrated into the V-cycle that underpins the model-based development technique for the development of electric vehicles, and it also contributes to reduce fuel consumption and greenhouse gas emissions by understanding driver behavior and driving style.

The behavior and style of the driver can have a significant impact on the overall efficiency of the vehicle. For example, Eco Driving has the potential to reduce emissions by 15% [7]. Several studies have examined driver behavior and how it impacts on vehicle efficiency. Most studies have focused on 'offline' simulations [8, 9] which used computer simulations to predict the optimum driver behavior.

Besides the physical fundamental modeling of each sub-system of the vehicle and its powertrain, carried out in the previous chapter, the driving strategy significantly impacts the range of battery electric vehicles (BEV). In motorsport environment, a commonly used parameter to identify the vehicle's performance is called 'minimum lap-time'. However, the traditional method to find the minimum lap-time is usually performed by a human racing-driver or using the predictive methods after collecting data from real world. However, this is an expensive way of testing, both in time and in money.

In this chapter, a Human-in-the-Loop approach will be used to examine the driving strategy for the Ene-1 GP SUZUKA competition. This challenge is similar to those related to commercial vehicles.

The literature related to human-in-the-loop is limited. Jameson et al. [10] used a human-in-the-loop to study the impact of different technologies to modify driver behavior of a conventional ICE vehicle. However, the research in using Human-in-the-loop to study the optimal driving behavior related to electric vehicles is limited. This research aims to address this.

The chapter is organized as follows. Section 2 provides the driving strategy review. Human-Hardware-in-the-Loop architecture given in Section 3. The limitations and further work are presented in Section 4. Finally, Section 5 concludes this chapter.

2. Driving strategy review

There have been numerous studies focused on improving driving strategy, so called 'eco-driving', with conventional ICE vehicles [11, 12]. However, the findings cannot be directly applied to hybrid electric vehicles (HEVs) or full-electric battery electric vehicles (BEVs). This is because the scope for eco-driving in conventional vehicles is fundamentally limited by the fuel-consumption which is principally affected by the throttle position and gear selection.

Hybrid vehicles require the most complex strategy to optimize energy usage, since the powertrain is the most complex, with the interplay between the ICE, electric motor and bidirectional energy flow from the batteries. Franke et al. [13] studied the driving strategies of efficient drivers of hybrid vehicles. They stated that key to efficient driving of hybrid vehicles is a technical knowledge of the powertrain system and being able to adapt the driving style to the changing environmental conditions. The work also presented recommendations that would allow drivers to adopt eco-driving behavior, and these included transparent and comprehensive feedback of the powertrain and energy usage.

With the regenerative braking function on BEVs, the studies examining eco-driving with internal combustion ICE vehicles cannot directly correlated to BEVs [14].

The BEVs powertrain architecture is less complicated when compared to other powertrains (ICEs, HEVs). However, as discussed, optimal driving strategies can significantly reduce the energy consumption and improve the range of BEVs. Therefore, in this section, a brief review of driving strategies is discussed.

Existing research of driving strategy investigations have mainly focused on safety concern, the most common commercially available today is Adaptive Cruise Control (ACC) which is based on robust control theory. In principle, ACC is able to control the vehicle by automatically adjusting the vehicle speed to maintain a safe distance from vehicles ahead only in the longitudinal direction. However, when the vehicle is experiencing a steering change, the target velocity of ACC needs to be lowered in order to keep the lateral acceleration within safety limits. Thus, unexpected change might cause ACC an error.

For this reason, Volkswagen introduced a Green Driving strategy [15] that integrated the predictive information from the upcoming diving environment into the ACC system. However, these systems only determine a local energy optimal driving strategy based on the restricted available information about the upcoming route without considering the impact of requirements of the global energy and time demand.

Zhang et al. [16], proposed a new approach to enhance the driver-individual driving strategy by observing and learning the driver's preferences. Two concepts of self-learning algorithms respectively based on dynamic programming (DP) and Q-learning (reinforcement learning) were developed to realize the approach.

In Choo's research [17], a machine learning software was developed at MIT for professional racing to improve the predictions of track position changes within a race. As shown in **Figure 1**, several factors that will possibly affect the racing performance were considered to analyze the system dynamics causality of race characteristics.

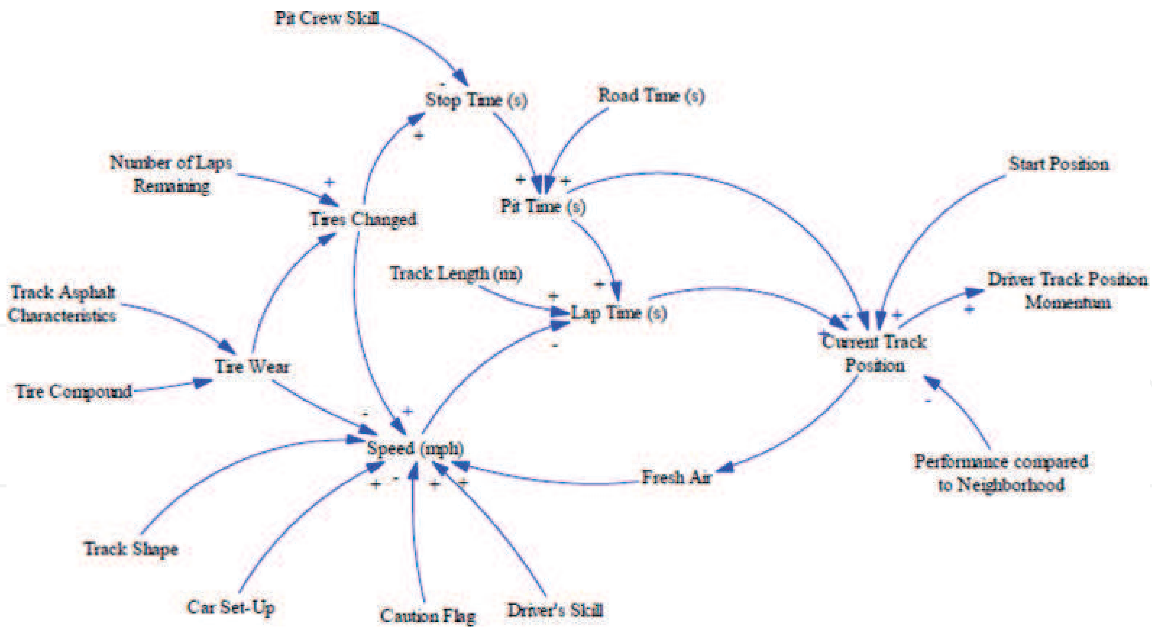

Figure 1.
System dynamics causal loop diagram of race characteristics affecting track position [17].

In general, the driver with the lowest cumulative total lap time throughout the course of a race is expected to win the race.

Hu et al. [18] investigated the driving control strategy of a battery electric bus by fuzzy logic control (FLC) algorithm, the findings show that proposed method has excellent output torque control of the electric machine and vehicle driving dynamics and acceleration performance are improved.

Another driving strategy example has been applied in Shell Eco-marathon competition [19] and successfully won the first place in the race. In their research, based on the experimental results, they examined the impact on racing time by varying the range of vehicle speeds in order to determine the most efficient fuel cell operating condition.

3. Human-hardware-in-the-loop architecture

Figure 2 shows the basic integration of the vehicle model (developed in the previous chapter) with a human driver. The input block reads the 'human' input data from the physical environment; these include steering angle, throttle and brake position and gear selection. The vehicle model then calculates the outputs; such as vehicle kinematics and powertrain properties. The vehicle model also includes information from the simulator domain, such as road gradient based on vehicle position. The outputs from the vehicle model are then used to determine the new vehicle position in the simulator domain. At the new position, information is passed back to the physical domain, such as the graphics for the user display, force feedback in the steering wheel, and some basic haptic feedback for the driver based on road noise.

For the experiments, in this chapter, simulation software called Panthera developed by Cruden was used. It runs the physics and graphics engine as well as communicating with the motion-based platform. It is used for real time simulations in Human-in-the-Loop simulators. **Figure 3** shows a screenshot of the virtual environment from inside the Cruden Software.

The physics model used was the same as discussed in the previous chapter. The vehicle was controlled using a Logitech G920 steering wheel, pedals and manual gear shifter. The steering wheel offered force feedback to improve the realism. The simulator did not use any motion or any other vestibular cues. Telemetry data from the simulation environment were recorded using the inbuilt application at a rate of 100 Hz.

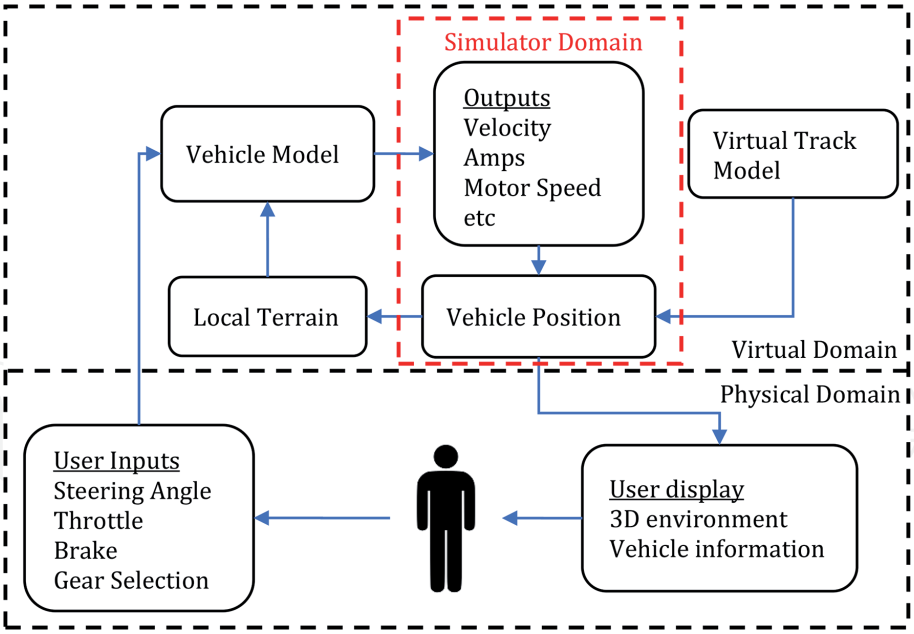

Figure 2.
Overview vehicle model integration in the simulator.

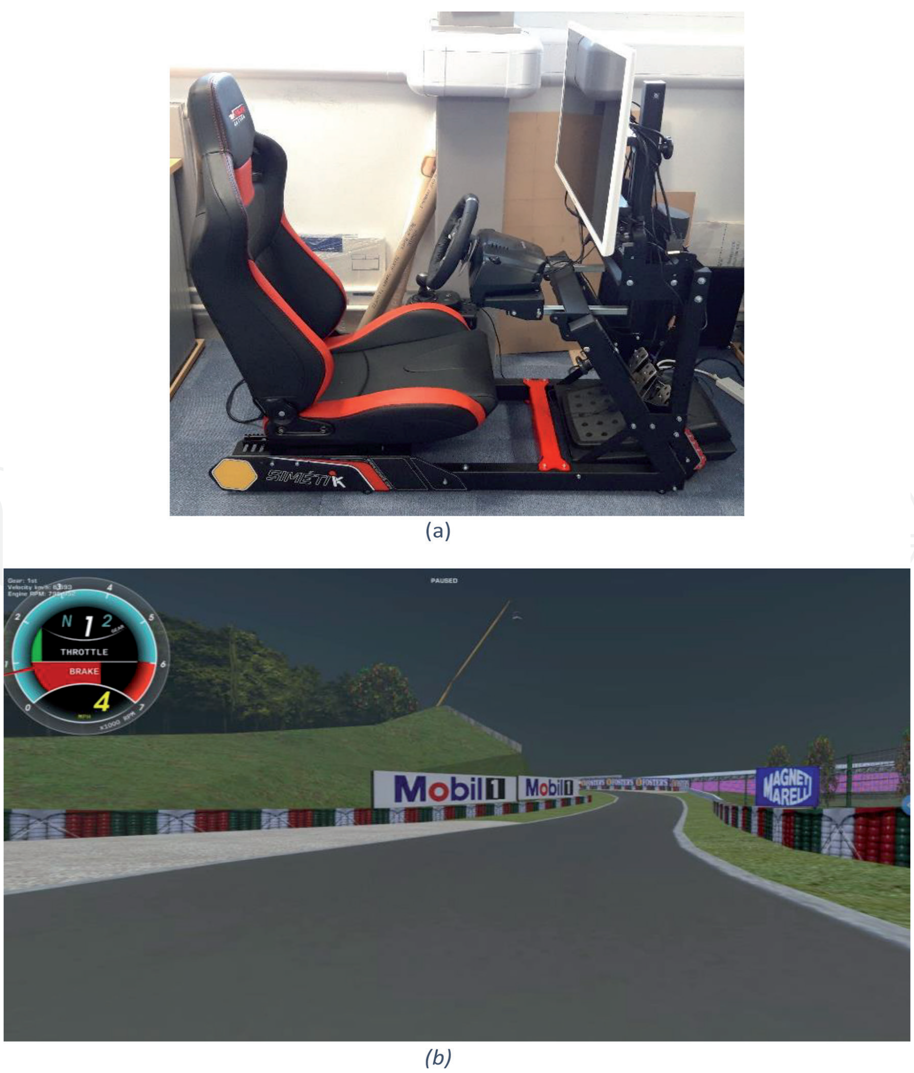

Figure 3.
(a) Simulator setup (b) screenshot of virtual environment of Suzuka F1 circuit.

Parameters	Symbols	Units	Values
Vehicle mass (with driver)	m	kg	77.48
Tyre rolling radius (front, rear)	R_{wheelf},R_{wheelr}	m	0.17
Aerodynamic drag coefficient	C_d	—	0.62
Vehicle frontal area	A_f	m^2	0.5
Density of air	ρ	kg/m^3	1.25
Acceleration constant	g	kg/m^2	9.81
Tyre rolling resistance coefficient	C_{roll}	—	0.026
Front track width	t_f	m	0.656
Wheelbase	L	m	2.956

Table 1.
Input parameters for vehicle model.

The input parameters into the model are shown in **Table 1**.

The vehicle had eight gears with final ratios of 7.76, 6.35, 5.47, 4.81, 4.10, 3.34, 2.88 and 2.53.

In the first chapter, the battery current (throttle pedal) was inputted into the model based on real-world data. The gear was selected, based on simple thresholds of maximum and minimum motor speeds.

However, the advantage of having a human in the loop is that they can make more complex decisions such as

- Change gear based on a range of variables such as current speed, current throttle position.

- Use knowledge of the route (track) to predict/anticipate the vehicle inputs required to meet the coming features. E.g. lift off the throttle in anticipation of a down-hill slope.

- Drive to a prescribed strategy.

To demonstrate the applicability of human-in-the-loop virtual environments for Electric Powered-Mobility Development, a case study of an electric race vehicle driving around the Suzuka race track was used. For the current study the impact of different target currents on vehicle velocity and battery SOC were evaluated.

The human driver was free to decide on their gear strategy as long as the target battery current was adhered to. A simple algorithm in the plant model acted as a current controller and allowed the driver to vary the current from 0 to 10 A with the throttle pedal.

The target currents that the driver was instructed to maintain were 5A, 6A, 7A, and 8A, respectively.

4. Results and discussion

To assess the impact of including the human-in-the loop the results were compared against computer simulations in which the current was maintained constant at the specified value. In this analysis, the computer-in-the-loop will be referred to as the 'computer driver'.

Figure 4 shows the variation of current, vehicle velocity, gear position and battery state of charge against distance for both the human-in-the-loop and computer-in-the-loop fixed current runs for the 8A target.

Figure 4a Shows that the target current of 8A was mostly adhered to by the human driver, with notable exceptions such as the lifting off around 2.5 km on the approach to a hair-pin bend. The results show that although slightly different throttle and gear positions were selected the velocity profiles are very similar resulting in a similar trip duration. Consequently, overall the energy usage of the human driver is similar with the human driver achieving a slightly better final battery state of charge of 45% compared to 43%.

As discussed for the 8A target run, there was little impact of having the human-in-the-loop compared to having the compute-in-the-loop. However, due to the nature of the route used as a case study, Suzuka circuit, optimizing energy usage is difficult due to the topology, as this circuit has some challenging aspects to it. In particular, there is a steep climb of over 35 m starting at a distance of 900 m, as shown in **Figure 5**.

It was found that for both the computer-in-the-loop and the driver-in-the-loop tests that it was not possible to overcome the gradient and 35 m hill-climb for the 5A and 6A test runs. Therefore, at these sections it was required to increase the current (throttle position) to prevent the vehicle from coming to a standstill.

Figure 6 shows the variation of current, vehicle velocity, gear position and battery state of charge against distance for both the human-in-the-loop runs and computer-in-the-loop fixed current runs for the 5A target.

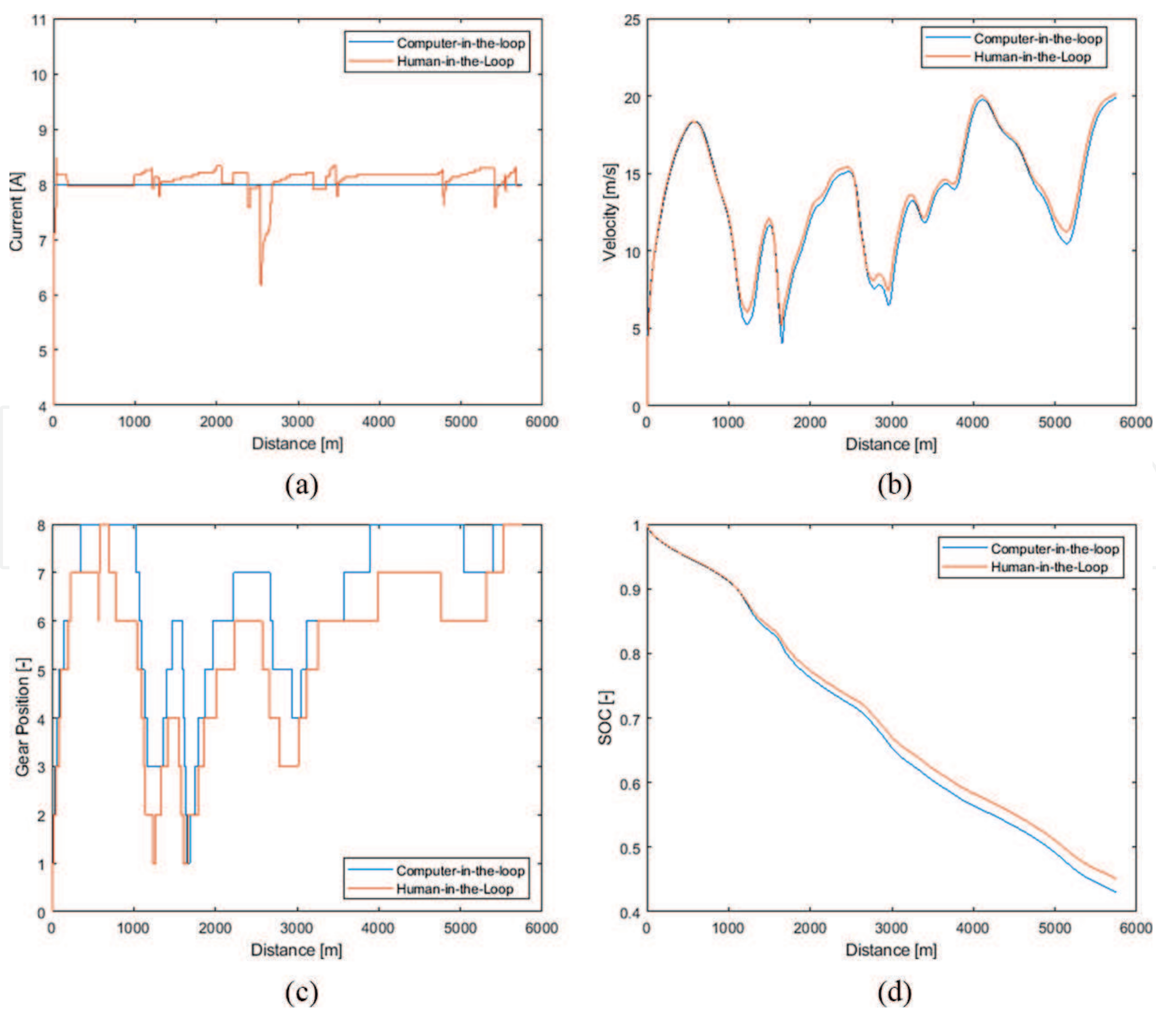

Figure 4.
Variation of (a) Current, (b) vehicle velocity, (c) gear position and (d) battery state of charge against distance for both the human-in-the-loop runs and fixed current runs for the 8A traget.

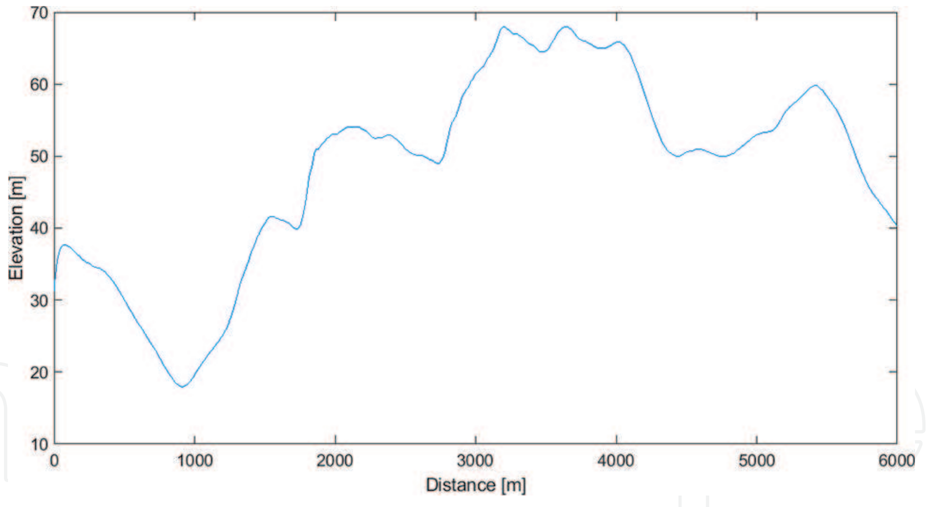

Figure 5.
Variation of elevation with distance.

Figure 6a shows that for the human driver a current of 10A (full throttle) was required to ensure that the vehicle made it over the crest of the hill. **Figure 4a** shows that full throttle was not necessary for the 8A test. This is due to the higher initial target current because of this the vehicle reaches the bottom of the climb with a higher velocity (**Figure 4b** and **6b**) and therefore has sufficient momentum to reach the top of the climb without demanding additional current.

The additional demand from the motor (full throttle) in the computer-in-the-loop tests was simulated with a simple step function. The duration of this step was determined by manually iterating the duration until the vehicle just cleared the crest of the hill. This was achieved as shown in **Figure 6b** where at around 1700 m the velocity of the vehicle almost reaches a standstill.

It can be shown in **Figure 6a** that full throttle is applied by the computer driver much earlier that the human driver. The reason for this is that the torque applied to the wheel of the vehicle is a function of the gear ratios as well as the torque from the motor.

Figure 6c shows that the human driver changed down through the gears much more quickly than the computer driver. The gear selection strategy for the computer-in-the-loop tests was the same as the one employed in the previous chapter. That is that the computer driver selected the gears to keep the motor speed within a set range. Because of this strategy, this meant that the computer driver changes gears later than the human driver.

This highlights the importance of having a human-in-the-loop whilst testing these technologies. The human driver had the foresight to select a lower gear in anticipation of the upcoming steep climb. To develop an algorithm for the computer-in-the-loop tests that could replicate this human behavior would be challenging. It would also unlikely to have the versatility to be applied to different scenarios where the circumstances are different.

The outcome of demanding full throttle for longer is that the final state of charge of the battery is much lower for the computer driver than for the human driver. **Figure 6d** shows that the final battery state of charge for the human and computer driver is 51% and 40% respectively.

Table 2 shows a summary of the final battery state of charge for each of the target currents for the human and computer driver. The results show that, generally, the state of charge increases as the target current decreases. This result is intuitive as running at a lower current will demand less energy from the battery.

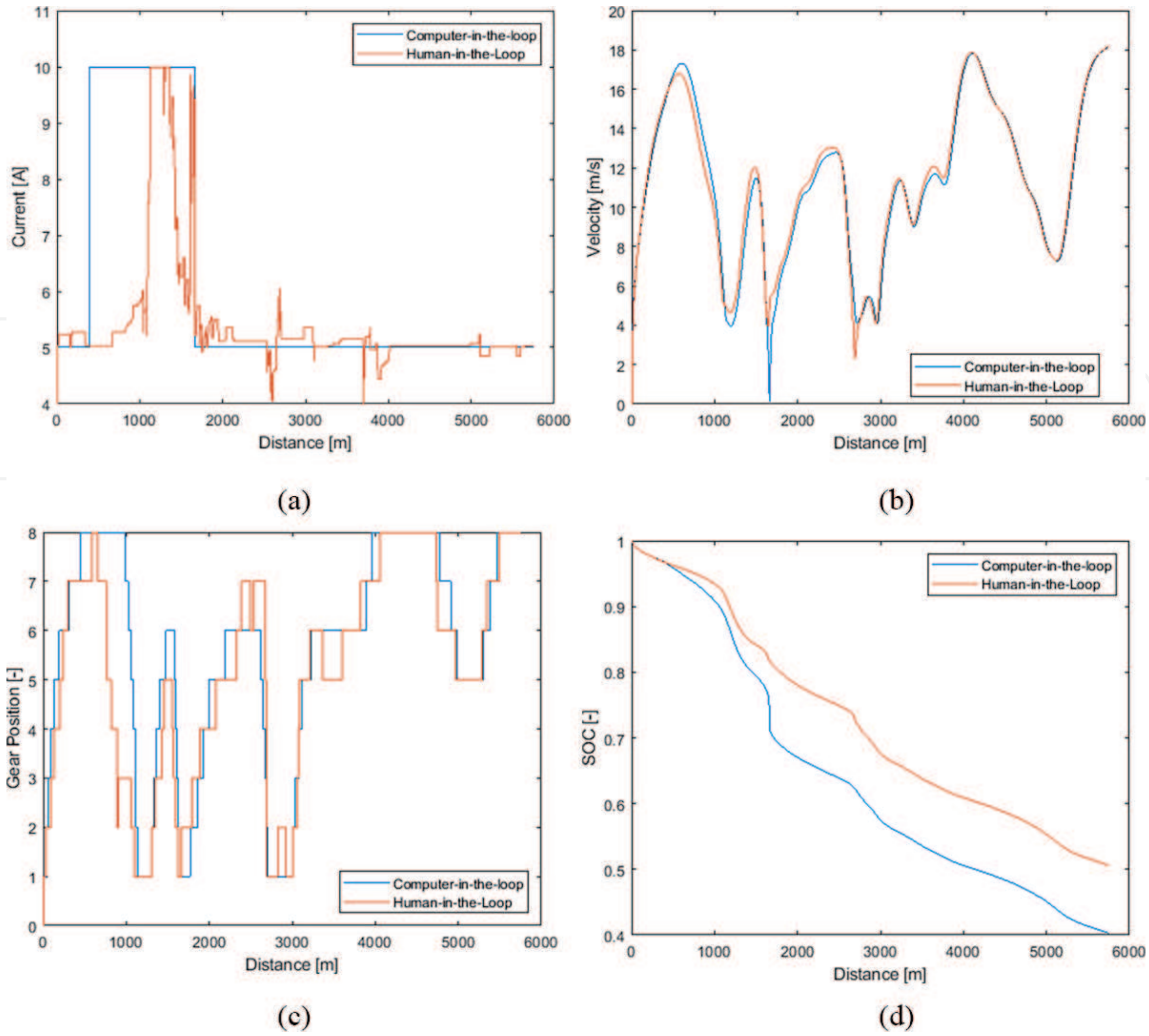

Figure 6.
Variation of (a) Current, (b) vehicle velocity, (c) gear position and (d) battery state of charge against distance for both the human-in-the-loop runs and fixed current runs for the 5A traget.

	Final SOC (%)	
Trial	**Computer driver**	**Human driver**
5A target	50.6	40.3
6A target	49.4	36.5
7A target	47.4	46.3
8A target	45.2	43.2

Table 2.
Summary of energy used for each of the target trials.

The results also show that in every case the human driver was able to optimize the energy better than the computer driver. The difference between human-in-the-loop and computer-in-the-loop is not constant. The impact of the human driver is more pronounced at lower target currents, a significant result when trying to optimize energy usage.

However, there is a tradeoff between target current and mean speed. In some instances, the mean velocity of the vehicle may not be a concern and therefore energy optimization is the primary concern. More likely, especially when this technology is being implemented in the public domain, a significant reduction in mean velocity is not acceptable, and a compromise is required.

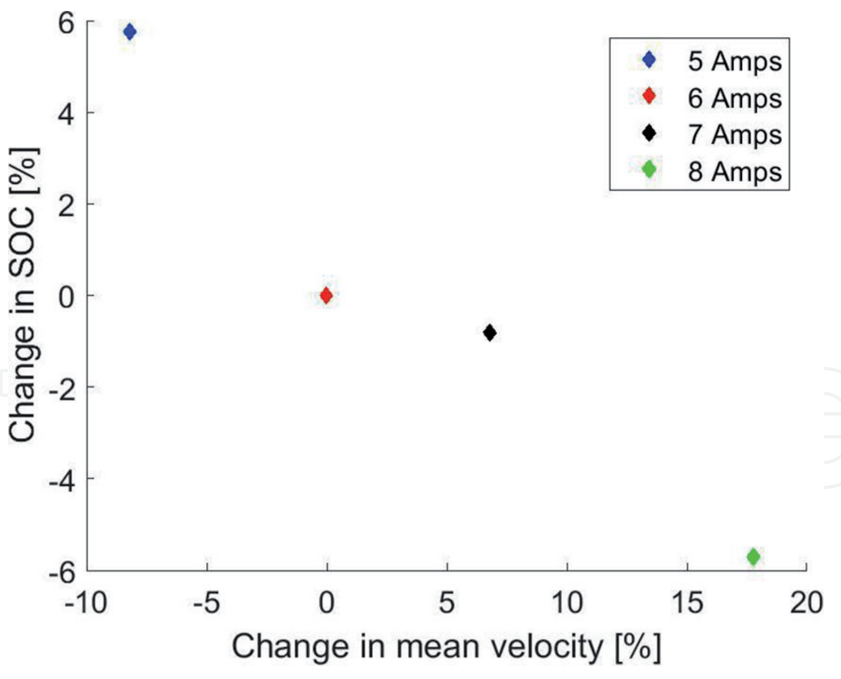

Figure 7.
Variation of change in final SOC with change in mean velocity for target currents of 5A, 6A, 7A & 8A.

Figure 7 shows the variation of change in final SOC with change in mean velocity for target currents of 5A, 6A, 7A & 8A. Generally, as expected, the final percentage change in final SOC decreases and the mean velocity increases as the target current is increased. However, there is a point of inflection in the trend between target currents of 6A and 7A. This shows, based on the data that increasing the target current from 6A to 7A has an appreciable change in mean velocity without a significant penalty in final SOC.

5. Limitations and further work

It should be noted that principally this study is a pilot study to examine the feasibility of using driving simulators to study the impact of having the human-in-the-loop to develop and optimize strategies to save energy from electric vehicles. This has been successful, and there are a number of limitations that prevent wider conclusions being drawn.

- The sample size is small with only four tests

- The sample were told about the research in advance and hence may have influenced their behaviour

To build on the research in this chapter a range of activities are planned as further work, these include:

- Testing alternative energy optimization strategies, such as limiting motor speed or vehicle acceleration.

- Include a larger range of tests, with statistical analysis, to limit the variability of human driver behavior.

- Incorporate hardware into the loop so that human-hardware-in-the-loop studies can be informed.

6. Conclusion

This chapter presents the evaluation of a Human-Hardware-in-the-loop architecture for Future Electric Powered-Mobility Development. To demonstrate the architecture a simple strategy of driving to a target battery current was employed. The results were compared to the results from computer-in-the-loop trials with the same conditions. The main conclusions are:

- The architecture allowed for good quality comparative data to be collected and driving strategies to be evaluated.
- The data showed that at relatively high target currents there was a marginal positive impact of the human driver compared to the computer driver.
- When running at low current targets, to conserve as much energy as possible, the human driver had a significant positive impact compared to the computer driver.
- The reason that the human driver was able to conserve more energy was due to anticipation of the upcoming gradient and better gear selection strategy.
- The data showed that, as expected, the mean driver velocity increased with the target battery current.
- The variation in mean velocity and SOC show an inflection point meaning that that increasing the target current from 6A to 7A has an appreciable change in mean velocity without a significant penalty in final SOC.

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