Range extended engine management system for electric vehicles: Control design process

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In this work a research is presented aimed to improve the mechanical performance models used to establish a range-extension methodology, and to introduce the use of computational intelligence to operate a real-time range extension engine management system to replace the current algorithmic approach. This paper describes the initial stage in design of the control strategy, taking into account a number of environmental factors in order to increase the range of series hybrid electric vehicles.

Topics / Pure electric vehicles, Hybrid electric vehicles and Energy-efficient vehicles

1. INTRODUCTION

One of the major barriers to the market take-up of electric vehicles (EV) is the short range of use between battery charges. Unlike fossil fuel vehicles, recharging is not a fast process (taking up to 12 hours), and the shortage of charging points away from urban centres means that users are resistant to use EVs for long trips that are at the limit of their range capability. Such a range anxiety can be overcome by encouragement from governments; e.g. in UK a 25% discount up to a maximum of £5,000 is offered to new EVs buyers [1].

Still, such encouragement might be not enough to alleviate the range anxiety among electric vehicle users and it should be accompanied with the demonstration of advancements in electric and hybrid vehicles technology. While the main strategy to increase take-up of EVs is deployment of extensive charging infrastructure, another solution to the range anxiety conundrum is use of the range extenders. Indeed, EVs with built-in range extenders are now available for drivers. Cars like Vauxhall Ampera, Chevrolet Volt or BMW i3 are examples of the recent efforts carried out by the automotive industry to bring the range extender technology to the EV market. Also, among researchers in academia the range extender concept has been of particular interest in recent years; e.g. [2, 3, 4, and 5].

The range extender concept is predominately based on series hybrid architecture. A schematic for such a powertrain configuration is shown in Fig.1. In series hybrid electric vehicle (SHEV) there is no mechanical link between the range extender and drive train. Such configuration enables internal combustion engines to run in their highest efficiency while maintaining the battery charge level via a generator. The drive train is driven by an electric motor that requests the electric power from the battery and generator.

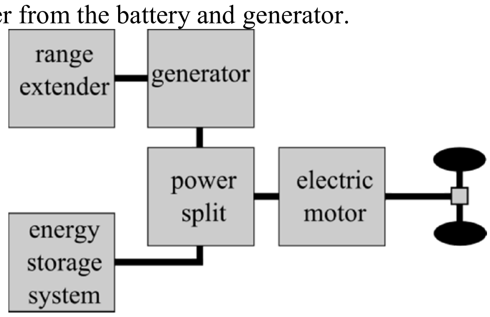

Fig.1 A schematic of powertrain configuration in a series hybrid electric vehicle.

A number of criteria needs to be considered in assessment of the electricity generation technologies for potential range extenders. The evaluation needs to consider efficiency, power density, packaging, production cost, emissions, flexibility of fuel, scalability, dynamics, noise, vibrations and harnessing [4]. The candidate technologies include internal combustion engines (ICE), fuel cells (FC) or micro gas turbines. However, the ICEs, due to their popularity and large number of variants are mainly investigated as the range extenders [2].

To handle the inherent complexity of range-extended electric vehicles (REEV) an on-board supervisory system is needed. In recent years several strategies for efficient operation of hybrid electric vehicles (HEVs) have been proposed with use of dynamic programming [6], equivalent fuel consumption minimisation [7], model predictive control [8], genetic algorithms [9], fuzzy logic [10] along with their variants and hybrids. For more details on the mentioned techniques see [11, 12] and the references therein.

However, the existing range extension algorithms typically monitor only the battery charge level

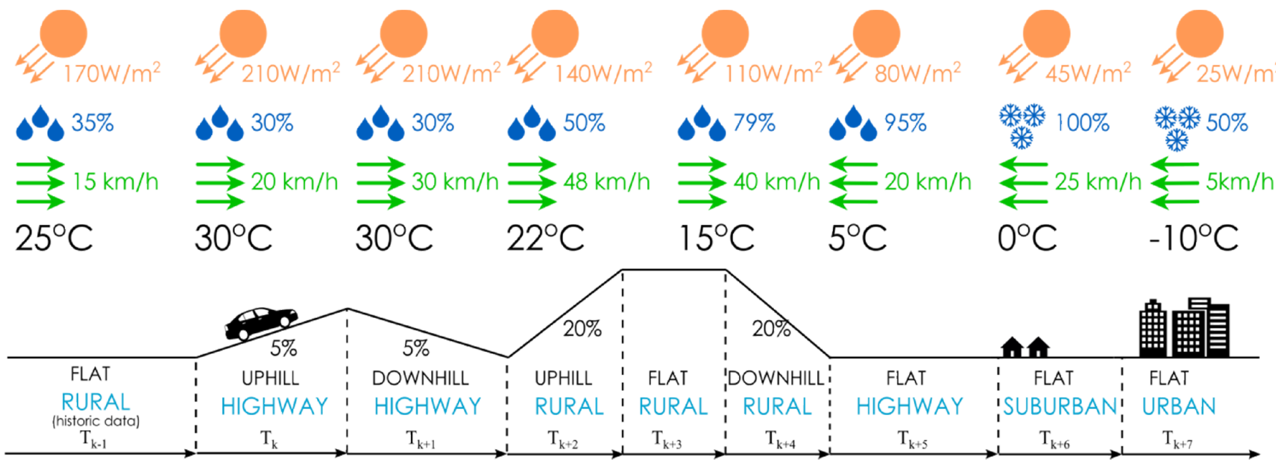

Fig. 2 Illustrating the external factors effecting the range of EVs including solar radiation, humidity, wind speed and direction, ambient temperature, road grade and road type. When journey is know in advance it can be divided into sections according to different factors values. In the above figure notation T_k identifies a current section. Index (k-1) refers to the set of historic data associated with the actual driver. In turn, (k+1) and so on refers to the next sections of the trip. When journey destination is unknown the strategy will incorporate available meteorological and GIS data in the arbitrary proximity to the actual vehicle location acquired from the GPS information.

regardless of the current and imminent load requirements [13, 14, and 15]. Some also take no account of energy recovery mechanisms such as brake flywheels. These approaches are valid, but inefficient as the vehicle's performance in real-world is affected by many additional factors including environmental conditions (e.g. solar radiation, humidity, wind direction, ambient temperature), journey characteristics (e.g. length, incline, road type (highway, suburban, urban)), driving style (aggressive, normal, eco), vehicle states and parameters (power demand, auxiliary and accessory loads, vehicle components' efficiencies).

Additionally, driving cycles created to evaluate performance of conventional vehicles are not applicable to emerging HEVs as they are inaccurate in real-world driving conditions [16] e.g. they often do not consider a load due to air conditioning. Hence, they are inadequate to predict the realistic power demands of EVs which is essential for development and evaluation of energy management strategies. Within this paper, we present an approach whereby a research electric vehicle is equipped with devices to capture the real world driving operation to capture a holistic set of parameters.

The paper is structured as follows. Section 2 is focused on identification of factors that effect the range of electric vehicles. This is followed by a brief description of the data acquisition system in Section 3 and design of the underlying framework for an energy management system (EMS) in Section 4. Section 5 concludes this paper.

2. IDENTIFICATION OF FACTORS AFFECTING HEVS PERFORMANCE

The control strategy design was initiated through the need for the identification of factors that effect the range of EVs. This section aims to assess the driving environment, the driving style of a driver and vehicle performance to determine an appropriate energy management strategy. One of the crucial elements of such a strategy will be an estimation of the remaining driving range for the EV, which, due to many different and varying factors, is difficult to predict precisely. The recent approaches focussed on increasing the number of factors in order to predict the EV range more accurately [17, 18]. Fig. 2 illustrates an example journey with a set of identified external elements that directly or indirectly act on the electric vehicles operation. Fig. 2 concerns only external factors but the list should be extended to include a driver behaviour and vehicle states and parameters. Description of the factors with the most significant impact is given below.

2.1 Ambient temperature, humidity and solar radiation

The effect of temperature and humidity on the ICE operation has been known for many years; e.g. higher humidity results in lower NOx emissions [19] or faster battery aging due to hot temperatures [20]. [21] investigated the cold and hot temperature effects on the HEV operation and efficiency. [21] reported that while the both tested vehicles performed very well in the extremely wide range of temperatures, their fuel economy was dramatically affected (2x) at low ambient temperatures because of the battery characteristics and operation. Ambient temperature, humidity and solar radiation have also an indirect effect of on the EV range due to possible air conditioning adjustments. Additionally, the data about the aforementioned factors would be valuable for estimation of the battery degradation, e.g. events like a fast recharge on a hot day would have a prolonged effect on the battery life cycle. Furthermore, the vehicle to be used to collect real-world data is equipped with a small solar panel. The solar radiation data might be used to predict how much of additional energy for low voltage vehicle accessory can be provided.

2.2 Wind speed and direction

A strong wind against the vehicle movement can increase the power demand of a vehicle especially in high speed driving on highways [22]. The impact of wind and speed direction was included in the intelligent energy management system developed by [23] for parallel hybrid electric vehicles. However, real data was not captured but instead artificial 3-D realistic roads were created with wind speed and directions incorporated. Simulations in [23] demonstrated that taking into account the combined wind/drag, slope, rolling, and accessories loads fuel consumption can be minimised under various specific driving conditions. In the control scheme proposed within this paper, the journey speed and direction will be compared with the current wind speed and direction forecasts for the vehicle vicinity.

2.3 Road type, incline and traffic congestion

A number of studies demonstrated that energy consumption for driving in cities centres is higher compared to driving in suburban or rural locations. This is mainly due to increased traffic congestion, traffic signals and a need to react to other drivers' manoeuvres. [24] reported that for city driving, intense traffic increased the fuel consumption by 20-45%. In turn, when driving on a highway, the choice of cruise speed by the driver has the major impact on the vehicle energy demand. [23] included the road slope as a major factor contributing to energy consumption in their intelligent control of the operation of a hybrid electric vehicle. Especially in mountainous areas correctly allocating electric energy for downhill or uphill part of the journey would improve the efficiency and battery health. When a journey is planned ahead, obtaining the elevation is straightforward but when a destination is unknown the elevation can be provided with a GPS device.

2.4 Auxiliary and accessory loads

The auxiliary load in HEVs usually include a power demand from the heating, ventilation and air conditioning (HVAC) systems, radio, etc., where the accessory load is due to power requirements for the vehicles housekeeping, power steering, headlights, etc. [25] indicated that HVAC systems can significantly increase the energy consumption of a vehicle and negatively influence its performance. For example, [26] reported that air conditioning loads can reduce EV range and HEV fuel economy by nearly 40%. In the research vehicle to be used in this study, the peak power of the HVAC is around 6kW, whereas the accessory load is around 0.2 kW. As the HVAC system is considered as the single largest auxiliary load it is crucial that its operation is monitored and if possible efficiently controlled. The high HVAC load is also the main reason for the inclusion of the external factors such as ambient temperature and humidity into HEVs operational control strategies in order to predict the use of HVAC in a journey ahead.

2.5 Driving style

Driving style has been considered one of the major impacts on the vehicle performance. Studies in [24] and [27] reported an increase of up to 40% in fuel consumption when comparing aggressive and normal style of driving. While these studies considered diesel and petrol cars only, it has been confirmed that the energy consumption in hybrid electric vehicles for aggressive style will be significantly higher than for normal or economic driving style. According to [24] driving behaviour can be classified as follows: (i) calm/economic driving that implies anticipating other road user's movement, traffic lights, speed limits, and avoiding hard acceleration, (ii) normal driving that implies moderate acceleration and braking and (iii) aggressive driving that implies sudden acceleration and heavy braking. The typical ranges of average accelerations for the particular style are presented in Table 1.

Table 1 Acceleration values in m/s^2 associated with driving styles [24].

Location	Economic	Normal	Aggressive
City	4.85-6.9	6.98-8.6	9.15-11.8
Highway	0.85	1.0	2.16

In the real-world, the driving behaviour is effected by many factors e.g. traffic, road conditions, duration of the trip, etc. While in some sections of the road certain level of similarity may be found in other sections it may significantly differ. As a result, methods capable of modelling various driving behaviours are critical for energy consumption analysis in HEVs. Here, it is proposed to log driver behaviour along with other factors in order to create a driver profile that, subsequently, will be used to predict driver style.

3. RESEARCH VEHICLE AND INSTURMENTATION

For the purpose of collecting real-world data, a Nissan Leaf car has been utilized. The research vehicle parameters are listed in Table 2.

Table 2 Research vehicle parameters

Chassis and body	Unit	Value
Drag coefficient		0.28
Rolling resistance		0.007
Frontal area	m^2	2.19
Kerb (dry) weight	kg	1521
Drive axle weight fraction		0.59
Wheel coefficient of friction		0.7
Tyre radius	m	0.316
Tyres		205/55/R16
Propulsion	**Unit**	**Value**
Motor type		PM AC
Motor peak power	kW	80
Motor peak torque	Nm	280
Energy storage system	**Unit**	**Value**
Type of battery		Lithium-Ion
Battery capacity	kWh	24
Nominal battery voltage	V	364.8
Maximum power	kW	90
Number of modules		48
Number of cells in module		4
On-board load	**Unit**	**Value**
Accessory power	kW	0.2
Auxiliary peak power	kW	6

In order to acquire real-time user and vehicle driving information the on-board diagnostic (OBD) device and GPS-built-in tablet are employed. Our data acquisition system consists of three main subsystems: (i) vehicle run-time monitoring devices that collect driving data from the OBD device, (ii) tablet with an application capable to collect detailed driving patterns and trip information using built-in sensors, such as GPS and accelerometer; and (iii) a remote computer server to store monitored information for further analysis and exploration. Figs. 3, 4, 5 and 6 show a real-world data collected from the OBD device. It is a sample of a typical daily use of the research vehicle by one of the test drivers. The data consists of different events e.g. three different short journeys or battery charging period. Such data are then subsequently processed within Matlab/Simulink environment.

Additionally, an engine dynamometer will be used to adjust the mechanical performance models and also to test developed control strategies in hardware-in-loop framework.

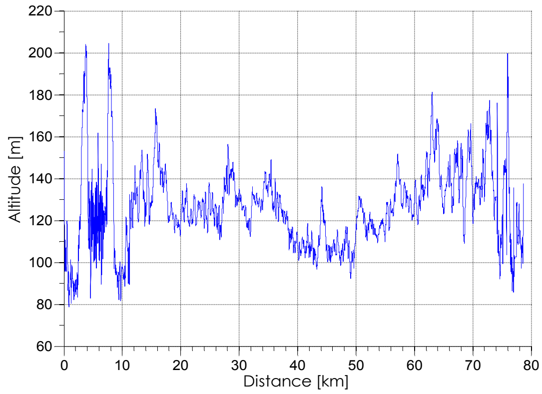

Fig. 3 Elevation change along a real-world journey.

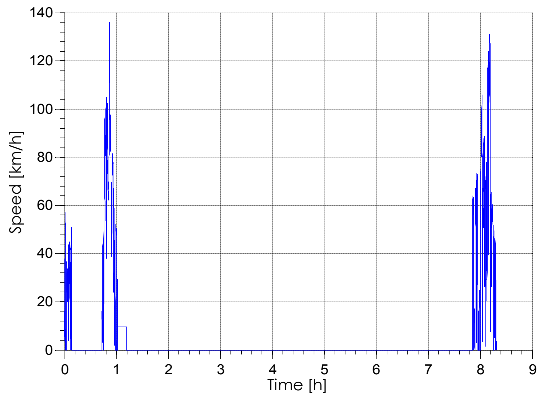

Fig. 4 Vehicle speed recorded via OBD device.

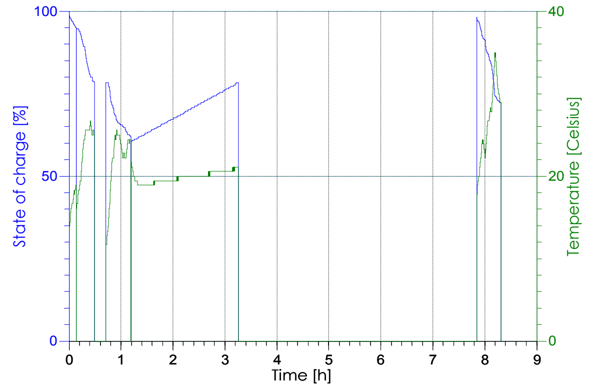

Fig. 5 Batteries temperature and state of charge acquired via OBD device.

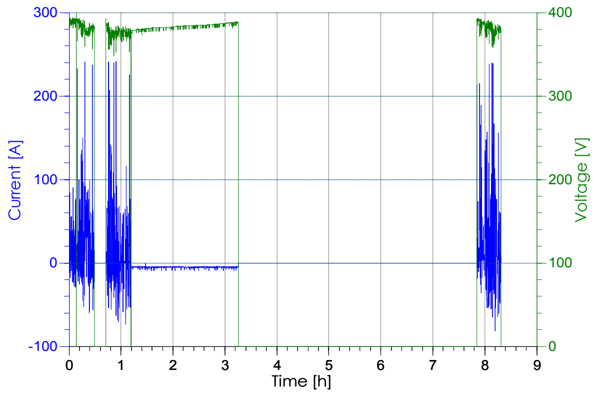

Fig. 6 Current and voltage acquired via OBD device.

4. DESIGN OF CONTROL STRATEGY

The aim of control strategy for range extended electric vehicle proposed here is to manage power distribution by controlling the current power delivery based upon real-time conditions and predicted near-time load changes. A review of different methodologies led to the conclusion that techniques from the computational intelligence (CI) domain will be suitable for the aims of this project; e.g. [25] demonstrated that look-ahead environment information can be employed by the intelligent energy management system to achieve reduction of energy consumption.

The proposed architecture of the range extended energy management system (REEMS) is illustrated in Fig.7. REEMS will use vehicle instantaneous demand, along with SOC as an input into the CI system that will optimize the power flow while considering the predicted journey-related power requirements, adjusted to the current driver behavior, against available stored energy.

The CI unit was based on the fuzzy logic concept whereas the prediction of journey power requirements and driving style recognition were developed with use of artificial neural networks (ANN).

Fuzzy logic transforms expert-based knowledge in the form of rules into a decision making system. The main advantage of fuzzy logic is that it can be tuned and adapted if necessary, thus enhancing the degree of freedom of control. It is also a non-linear structure, and that is especially useful in a complex system such as an

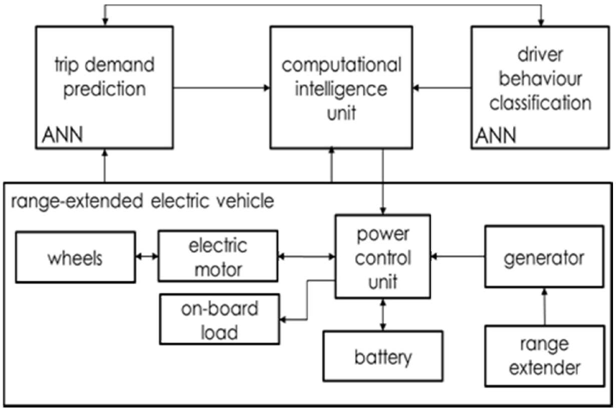

Fig. 7 Illustrating the proposed REEMS architecture.

advanced powertrain. ANNs with highly nonlinear and adaptive structure have been used in many applications. ANNs have inherent interpolation properties, so they are an ideal candidate for pattern recognition.

At this stage of the project, data from the real-world trials and measurements were not available, as trials with the Nissan Leaf were just starting and installation of the engine dynamometer was not yet completed. However, the proposed CI system subsystem was evaluated with use of artificially created data.

Figs. 8, 9 and 10 illustrate the impact of different factors on the mode of operation of the range extender. High SOC will keep the range extender off while demanding journey profile (TP) or aggressive driving style will switch the range extender on.

5. CONCLUSION

This paper presents the initial process of the control strategy design aimed to operate a range extended electric vehicle in an efficient manner while considering a number of factors that effect its range.

Impact of different external factors on the range of electric vehicles has been reviewed for a subsequent design of energy management strategy. This will enable energy management system to manage the available power more efficiently and thereby extend the range.

The proposed REEMS system was built upon fuzzy logic and ANN concepts enhanced with data from real world EV trials and high-fidelity performance models derived experimentally in De Montfort University Engine Research Laboratory using live data obtained from the vehicle CAN network and external sensors

Once the trials with the instrumented research vehicle has been completed, the system will be evaluated in simulations and the concept be extended to take account of additional factors and parameters.

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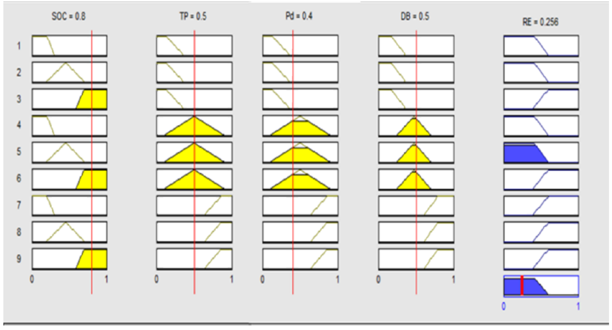

Fig. 8 Impact of SOC on the range extender operation.

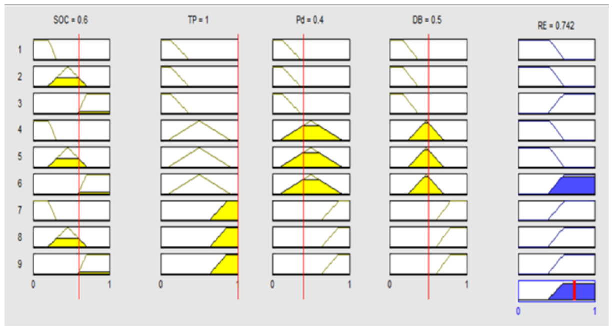

Fig. 9 Impact of demanding journey (TP) on the range extender operation.

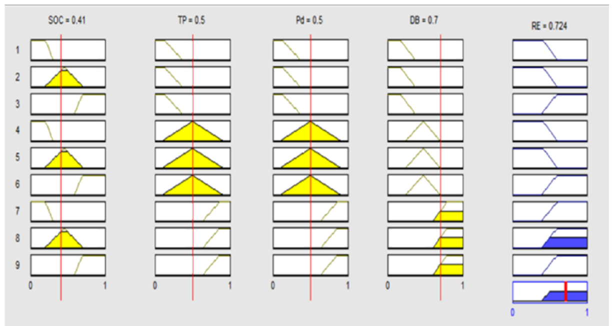

Fig. 10 Impact of aggressive style (DB) on the range extender operation.

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