Cloud Based Optimal Routing and Powertrain Management for Hybrid and Electric Vehicles

Can Kurtulus
Team Leader, SW & Controls, AVL Turkey
PhD Candidate, Istanbul Technical University
Istanbul, Turkey
email: can.kurtulus@avl.com

Gökhan Inalhan
Assoc. Prof., Aeronautical Engineering Department
Director, Controls and Avionics Laboratory
Istanbul Technical University
Istanbul, Turkey
email: inalhan@itu.edu.tr

***Abstract*— Hybrid and electric vehicles have been gaining significant traction in the vehicle market for the past few years, and this necessitates that further attention should be given to their unique characteristics. This paper illustrates a combined route guidance and power management approach, where the required computation is distributed across an on-board/off-board system architecture. A model of the vehicle and the powertrain is utilized to calculate arc costs of a road network for optimal route guidance purposes, and the calculated power reference is later on used for dynamic programming based power management. This approach has the potential to improve vehicle efficiency significantly, and an application scenario based on recorded real world trip information is used to demonstrate system operation.**

Keywords - hybrid-electric vehicles; powertrain management; vehicle route guidance; cloud computing

I. INTRODUCTION

Hybrid and electric vehicles have been gaining a large importance lately as the primary answer to the demands of ever lower levels of noxious emissions as well as lower fossil fuel consumption [1]. These vehicles either have an electric drive component in addition to the conventional combustion engine, or completely get rid of the combustion engine and have fully electric powertrains [2]. The higher efficiency of the electric drive, as well as the possibility to capture normally wasted kinetic energy (i.e., during braking), bring about a significant level of improvement in both fossil fuel consumption and noxious emissions. The main barrier holding back an even more widespread adoption of these types of powertrain configurations is the added system cost, especially for the battery, and the relatively lower energy density of electrochemical energy storage as opposed to fossil fuels, which in turn limits the range of electric driving. The resulting effect of the current situation is that utilization and flow of energy is an even bigger and critical concern for electrified powertrains as compared to conventional, combustion engine based ones.

This work builds upon previous results [3], that demonstrated an algorithm to determine the optimal route with respect to a composite cost function of distance, time, energy and battery wear, for a given source location and target destination pair in a road network. The approach to determination of the optimal route was Bellman–Ford–Moore (BFM) algorithm [4], which builds on the idea of dynamic programming applied to the shortest path problem [5]-[7]. This algorithm has a bound on worst case performance of O(mn) in graph of n nodes and m arcs. Another important feature of the previously reported approach was that external data sources enabled by the benefits of intelligent transportation systems – such as road topology, traffic and weather could be used as additional information to calculate the optimal route.

To be able to obtain the highest efficiency of hybrid electric vehicles, it is a prerequisite to have a combination of route guidance, and management of powertrain operation, which is a currently unexplored area of work. Past work has mainly focused on powertrain management of hybrid vehicles alone [8][9], or on determining the optimal path between two nodes in a road network with respect to time or distance [4] independent of the actual vehicle operation. The aim of this paper is to propose an architecture for this combination, and initial results, hence build upon previous work which focused on route guidance alone [3].

It is clear that for large road networks, which run into millions of nodes and several millions of arcs [10], it is not a straightforward task to compute optimal routes through the network, especially considering the fact that external data is incorporated into the calculation, and has to be processed in real time. For this purpose, it is proposed that the computation and memory intensive operations are shifted off board from the vehicle, to the cloud, and a simple communication strategy ensures that the optimal routing and powertrain operation is relayed to the vehicle, which has limited computing ability on-board.

The main theme of this work revolves around an integrated system architecture where a hybrid and electric vehicle focused route guidance is in constant interaction with hybrid powertrain management in a multi-layered fashion. The route guidance layer hinges on a model of the vehicle and the powertrain to determine energy efficient routes. This model, used to calculate costs for traversing the road network, is also important for the powertrain management

 ISBN: 978-1-61208-406-0

layer since expected future power profile during traversal of the route should be utilized to enable predictive powertrain management.

In Section 2, the problem is introduced, and the algorithm to find the minimum cost route through the road network, and power management is defined. In Section 3, the vehicle and powertrain model to calculate the energy costs for road network links is presented. In Section 4, the combined route guidance and power management algorithm is presented, and finally Section 5 gives an application example using a real world driving profile recorded from a trip, and the associated powertrain management strategy.

II. PROBLEM DEFINITION

A road network is a directed graph G{N,A}, where N is a set of nodes to represent road intersections, and A is a set of arcs to represent road segments connecting two nodes. Each edge of this graph, i.e., the arcs, represents a pair of connected nodes, (i and j), and is associated with a cost c_{ij} and arc(i,j) ∈ A. The shortest path is a sequence of arcs (a_1, a_2,..., a_n) ∈ A, that minimizes the total cost $\sum_{k=1}^{n-1} c_{i,i+1}$ over this sequence. The cost, c_{ij} is a weighted sum of distance, time, energy and battery wear where w_x are respective weights such that;

$$c_{ij} = w_d{*}c_d + w_t{*}c_t + w_e{*}c_e + w_b{*}c_b\,. \quad (1)$$

Previous work [3] demonstrated that equal weighting of all cost functions provide a well-balanced route in terms of time, distance, energy use and battery ageing that can serve as a basis for everyday driving. The weights can also be adjusted based on preferences of each driver.

Power management is the control of power and energy sources in a hybrid powertrain where the power demand of the vehicle is distributed to power providers according to pre-defined criteria. Fuel consumption is a widely used criterion [8], and the associated cost function can be defined as

$$J = \int_0^t \dot{m}_f\,(t, u(t))dt \quad (2)$$

where fuel mass flow $\dot{m}_f$ is minimized over the trip duration, *t*, via determining the optimal control sequence, u^*.

Dynamic Programming is a preferred approach for optimization based power management for hybrid vehicles, and the problem definition is already well covered in the literature [8][11].

III. VEHICLE AND POWERTRAIN MODEL

The vehicle and powertrain architecture selected for modeling is a range extended electric vehicle. This architecture is a part of the "Series Hybrid" family, where the combustion engine does not have a direct connection to the wheels, but drives a generator to support the electrical power network, and charge the battery whenever necessary. The main difference of this architecture to a battery electric vehicle is addition of a generator, which is comprised of a combustion engine, and an e-motor driven by that engine to support the power network. The architecture can be seen in Figure 1.

The powertrain components were modeled in a "Quasi-Static" fashion based on the concept of [12], which is the preferred approach for purposes of energy management and control. This approach neglects high frequency dynamics irrelevant to energy based modeling, and relies on look-up tables of powertrain components (e.g., engine, e-motor etc.) to relate power conversion and efficiency in a steady-state manner. These look-up tables are validated by test data, and dynamics are incorporated to a level they are necessary, such as battery state of charge (SoC) behavior, where the charge stored in the battery is modeled as a function of charge and discharge power of the battery over time, and battery voltage is related to SoC and power [13].

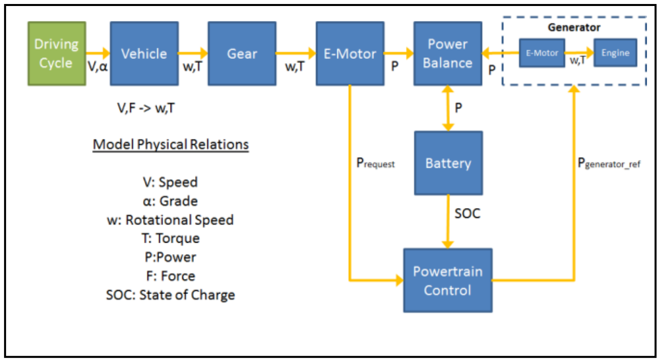

Figure 1. Powertrain and Vehicle Model Structure

The model was parameterized based on publicly available data for the Audi A1 e-tron [14], which is a good example of a range extended electric vehicle for urban use. The parameter set is listed in Table 1.

TABLE I. AUDI A1 E-TRON PARAMETERS

E-Motor		
Type	PMSM	-
Continuous Power	45	kW
Peak Power	75	kW
Range Extender		
Type	Wankel Engine	
Electrical Power	15	kW
Battery		
Capacity	12	kWh
Voltage	270	V
Vehicle		
Mass	1410	kg

IV. Route Guidance and Powertrain Management Algorithm

The overall route guidance and power management algorithm consists of a pre-processing and query steps.

Pre-processing step

- Input: Nodes and arcs of the road network,
- For every arc in the network, periodically carry out the following;
    - Acquire/load any additional data available for the network (e.g., topography, weather, traffic etc.). Data collection period depends on the type of data (i.e., daily for road work, 5 minutes for traffic, 15 minutes for weather)
    - Calculate the time to traverse each arc (might be different due to weather and/or traffic), if there is an update from the previous sample
    - Run the powertrain model to compute energy cost for each link, and post process simulation output for battery ageing calculation, as well as the composite cost.

Query step

- For the source and target nodes, calculate the optimal path with the least composite cost with BFM algorithm
- Run Dynamic Programming for the optimal path utilizing the pre-calculated power profile
- Send the path and range extender on and off command coordinates to the vehicle

The pre-processing step is run periodically for the road network of an area, and only the model based cost calculation of the step is specific to a particular vehicle, whereas the other steps are common for any number of vehicles, therefore benefit all vehicles that make use of the system. For a particular vehicle (or a family of vehicles sharing similar design parameters and powertrains), only the last step of pre-processing needs to be carried out, and it could also be possible to geographically constrain the evaluated arcs for cost calculation, due to the fact that it is usually possible to have knowledge of common and recent locations for a particular vehicle.

The link of route determination algorithm with the power management is through the vehicle and powertrain model and arc cost calculation, where the power demand profile to be negotiated in the calculated path was already found when calculating arc costs. This power profile is later on used to decide when to utilize the generator for range extension as part of a 2nd optimization step that is part of the powertrain management layer. The overall concept is shown in Figure 2.

The interaction between the vehicle and the cloud can be seen in Figure 3, where the vehicle handles user interface functionality to get the source and target locations, and carry out the range extender operation reference command based on location tracking to the range extender operation reference profile. All computations to determine optimal routes and range extender operation strategy are carried out in the cloud. In the case of relatively short trips, communication between the vehicle and the cloud would be necessary only once. Further communication to send route and range extender operation updates from the cloud could be needed for long trips, due to the fact that traffic and weather may change during the trip.

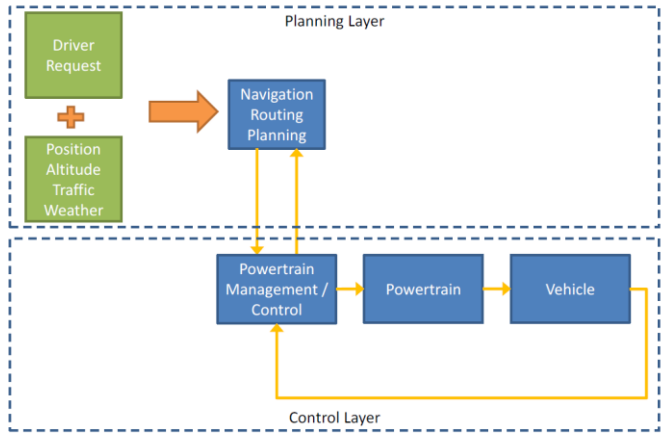

Figure 2. Multi Layered Architecture for Powertrain Management

V. Application Example

The application example is based on a real world recorded trip, where the route has been determined previously, and power management behavior is evaluated to judge feasibility of the approach. The trip route can be seen in Figure 4, and is nearly 64 km long. The route includes a large variation in altitude and speed, which makes it a good candidate to understand behavior of dynamic programming based operation control of the range extender.

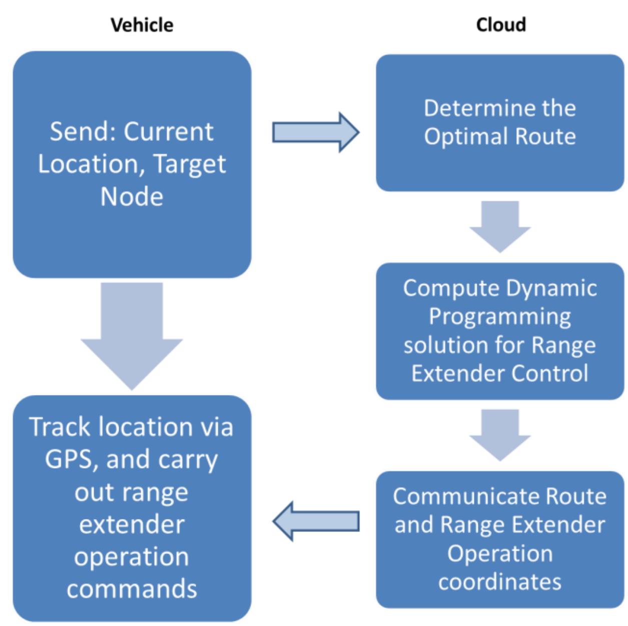

Figure 3. System Architecture

Figures 5 and 6 show the speed profile used during simulations in green (scaled 1/100 to fit in the same graph), battery SOC in blue, and finally the generator operation command in red (scaled by ½ to fit in the same graph). For comparison purposes, the same driving profiles were simulated with Charge-Depleting/Charge-Sustaining (CD-CS) control for generator operation that is used in Plug-in Hybrid Electric Vehicles (PHEV) and range extender electric vehicles (REEV). This strategy is a rule based one, and commonly used in industry as well as serving as the starting point for academic work [13]. The strategy is quite straightforward and aims to initially use most of the electric energy stored in the battery, called the "Charge Depleting" mode, and then switch to conventional hybrid vehicle operation, called the "Charge Sustaining" mode. In this second mode, the generator is operated to keep battery SOC around a pre-determined level.

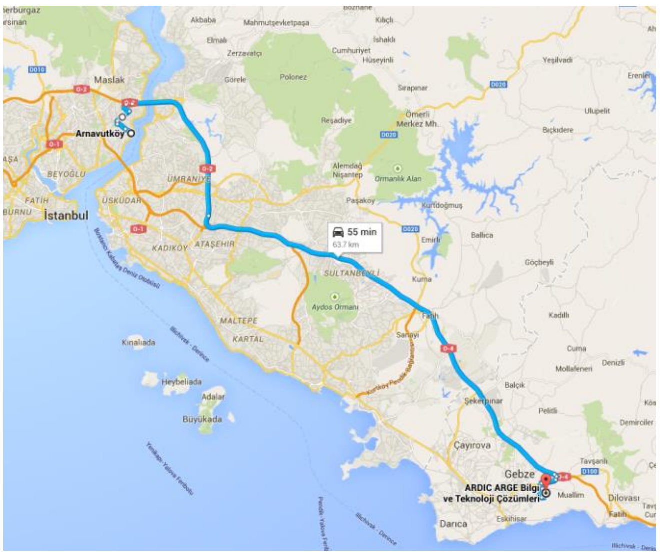

Figure 4. An overview of the route where the real world driving cycle was recorded.

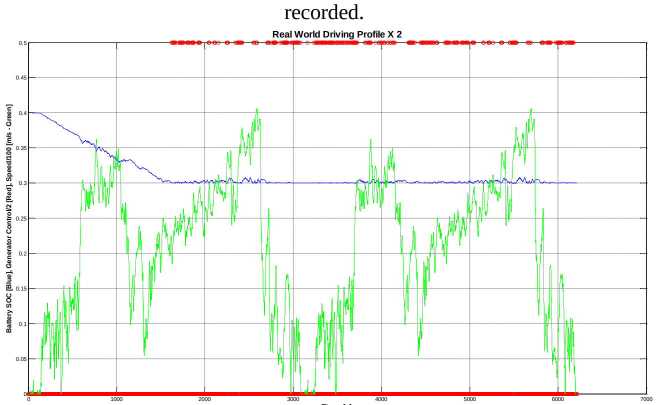

Figure 5. Figure 1 Generator operation and battery SOC behavior during a real world driving profile with CD-CS strategy

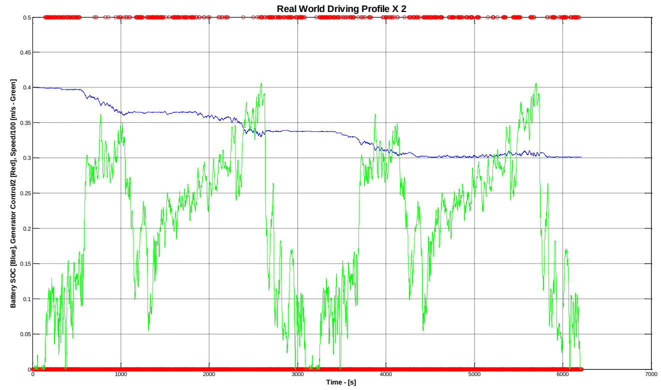

Figure 6. Generator operation and battery SOC behavior during a real world driving profile that minimizes fuel consumption

A quick evaluation of the results demonstrate key differences between a rule based decision on generator operation, and the operation strategy determined via dynamic programming. One of the significant differences is the starting point for generator operation. CD-CS strategy starts to operate the generator whenever the battery SOC drops below the pre-determined threshold (set at 30% for these simulations) as the name indicates, and continues to operate the generator to keep the battery at this threshold. Dynamic Programming based algorithm (DP) has knowledge of the complete driving profile, as determined already by the optimal routing algorithm, therefore starts to operate the generator much earlier during the profile to enable balanced operation of the battery and the generator as the energy source, and the battery reaches the pre-determined threshold significantly later during the driving profile. This contributes to the fact that battery is operating in a more efficient region for the duration of the trip, leading to lower fuel consumption, on the order of 3.7%.

VI. CONCLUSION

We have discussed a novel approach for combined route guidance and power management for hybrid and electric vehicles, carried out in an on-board/off-board coordinated computation architecture. This aspect has not previously been explored in literature, and is meant to serve as a starting point for further research where the interplay between route guidance and powertrain management will be explored in detail.

ACKNOWLEDGMENT

The authors would like to thank the anonymous reviewers for their constructive feedback, which helped improve presentation of ideas and overall quality of the paper.

REFERENCES

[1] G. Rizzoni, L. Guzzella, and B. M. Baumann, "Unified modeling of hybrid electric vehicle drivetrains," IEEE/ASME Trans. Mechatronics, vol. 4, no. 3, 1999, pp. 246–257.

[2] A. Emadi, K. Rajashekara, S. S. Williamson, and S. M. Lukic, "Topological Overview of Hybrid Electric and Fuel Cell Vehicular

Power System Architectures and Configurations," IEEE Trans. Veh. Technol., vol. 54, no. 3, May 2005, pp. 763–770.
[3] C. Kurtulus and G. Inalhan, "Model Based Optimal Route Guidance for Hybrid and Electric Vehicles," unpublished.
[4] B. V. Cherkassky, A. V. Goldberg, and T. Radzik, "Shortest paths algorithms: Theory and experimental evaluation," Mathematical programming, vol. 73, no. 2, May 1996, pp. 129-174,
[5] R.E. Bellman, "On a routing problem," Quarterly of Applied Mathematics, vol. 16, 1958, pp. 87–90.
[6] L. R. Ford and D. R. Fulkerson, Flows in networks. Princeton: Princeton University Press, 1962
[7] E. F. Moore, "The shortest path through a maze," Proc. Internat. Sympos. Switching Theory 1957, Part II. Cambridge, Mass.: Harvard Univ. Press, 1959, pp. 285–292.
[8] A. Sciarretta and L. Guzzella, "Control of hybrid electric vehicles," IEEE Control Syst. Mag., vol. 27, no. 2, Apr. 2007, pp. 60–70.
[9] S. G. Wirasingha and A. Emadi, "Classification and Review of Control Strategies for Plug-In Hybrid Electric Vehicles," IEEE Trans. Veh. Technol., vol. 60, no. 1, Jan. 2011, pp. 111–122.
[10] [Online]. Available http://snap.stanford.edu/data/roadNet-CA.html [Accessed: 09-Jan-2015].
[11] X. Zhang and C. Mi, "Vehicle Power Management," London: Springer-Verlag, 2011, pp 179-208
[12] L. Guzzella and A. Sciarretta, Vehicle Propulsion Systems: Introduction to Modeling and Optimization. Berlin, Germany: Springer-Verlag, 2007, p. 350.
[13] S. Stockar, V. Marano, M. Canova, G. Rizzoni, and L. Guzzella, 'Energy-Optimal Control of Plug-in Hybrid Electric Vehicles for Real-World Driving Cycles', IEEE Transactions on Vehicular Technology, vol. 60, no. 7, Jan. 2011, pp. 2949–2962.
[14] [Online].Available:http://origin-www.audi.com/etc/medialib/ngw/product/a1/a1/my_2010_catalog_images/pdf.Par.0009.File.pdf/2012_07_ams1512_120.pdf [Accessed: 09-Jan-2015].