

Runtime Power Management for Extended Range of Battery Electric Vehicles

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Abstract—Installation of a large-capacity battery pack is a straightforward method to extend the range of battery-electric vehicles (BEV, or all-electric vehicles.) However, at the same time, a large-capacity battery pack not only occupies a big space but significantly increases the vehicle weight, which directly impacts on the fuel economy and vehicle performance. This implies that increasing the battery capacity has an obvious limitation in extending the EV range. In this paper, we introduce a system-level framework that derives the minimum-energy vehicle velocity at each time instance (velocity planning) from the vehicle dynamics, electric powertrain characteristics, road slopes, payload, and consideration of regenerative braking. This work particularly takes into account driving time so that the resultant minimum-energy driving does not seriously slow down the vehicle.

The resultant velocity planning achieves range extension with the existing electric powertrain. The major technical contributions of this paper compared with the previous work include i) practically applicable minimum-energy velocity planning for production EVs from superb EV power model fidelity, ii) new performance metrics to consider both driving energy and driving time, i.e., energy-delay product, energy-square-delay product and energy-cubic-delay product that ensures both energy consumption and driving time, iii) comparative analysis of the minimum-energy velocity planning between EV and internal combustion engine vehicles (ICEV), and iv) analysis of the model fidelity impact on the minimum-energy velocity planning. The proposed method results in up to a 43.4% extended range and a 20.6% improvement of the energy-delay product compared with the best constant-velocity driving.

Index Terms—Electric vehicles, minimum-energy velocity planning, driving range extension

I. INTRODUCTION

Battery-electric vehicles (BEV) or all-electric vehicles are powered solely by the battery and thus generally cause range anxiety for most EV owners because their fully-charged range is much shorter than that of internal combustion engine vehicles (ICEV.) Lack of charging facility and longer charging time make the anxiety stronger, which is comparable to vehicle breakdown.

Unfortunately, it is hard to achieve a longer range from further efficiency enhancement of the major electric powertrain components such as traction motors, power converters, batteries, and so on, because they already exhibit a high efficiency (90% or higher), and thus the headroom for further enhancement is very narrow. A straightforward way to extend the range is to install a larger-capacity battery. However, this method does not only cause a higher manufacturing cost but

higher daily operating cost because it directly increases the vehicle curb weight, which is inversely proportional to the fuel economy [1]. Carrying a large-capacity battery also makes the passenger compartment smaller. In addition, the increased weight also directly impacts on the performance of the vehicle. EVs should be equipped with a more powerful drivetrain to compensate the weight increase, which again makes EV consume more energy. EVs deploy a large portion of light materials such as aluminum and carbon fiber to compensate the heavy battery weight not to degrade the fuel economy and performance significantly [2]. However, such a way also causes a significant manufacturing and repairing cost increase because light materials that ensure strength are generally very expensive and not repairable by sheeting. Such conventional ways to extend the EV range directly impacts on the cost of ownership.

We recently see a new initiative that attempts to reduce energy consumption of cyber-physical systems using application-aware cross-layer management. Such approaches apply algorithms, tools and methodologies relevant to design automation and embedded low-power systems [3]. Just naming several for instance, energy management for EV also considers drivers' behaviors and related EV power consumption to extend range [4], [5]. Electric vehicle battery packs consist of a large number of battery cells, and it is crucial to optimize the battery pack architectures in terms of capacity, cost and reliability [6], [7]. Electric vehicle battery management systems must be able to accommodate multi-power sources, provide a good scalability, and mitigate cell-to-cell variability [8]. Electric vehicles consume a non-negligible amount of battery energy for non-driving power components. Related study tries to optimize energy for heating, ventilation and air conditioning (HVAC) systems equipped in electric vehicles [9], [10]. A renewable energy aware pricing scheme minimizes both the community-wide electricity bill and individual electricity bill [11]. A hybrid energy storage systems improve efficiency and lifetime without significant increase of the cost [12], [13].

This paper introduces a runtime power management to extend the range without increasing the cost of ownership. EV energy consumption is largely different by the cruising velocity, acceleration, weight, load slope, etc. [2]. The concept of low-energy vehicle driving comes to reduce CO_2 emissions from ICEV. Lower CO_2 emission generally implies less fuel consumption [14]. However, low-energy ICEV driving results are not applicable to EVs due to significant differences between the engine and electric powertrain. An internal combustion engine with a transmission is a common ICEV powertrain structure while EV electric powertrain has an electric motor

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with a fixed ratio gearbox.

There have been low-energy driving research for EVs as well, but previous research relies on the vehicle dynamics models such as rolling resistance, gradient resistance, aerodynamic resistance, and so forth [15], which ignores loss of energy transformation from electricity to mechanical energy. Such simplification makes it impossible to differentiate EV from ICEV. It has been reported that even EV power models that consider the motor loss [16], [17], [18] can hardly reproduce correct EV drivetrain power consumption [1]. This paper demonstrates how incorrect EV power model can mislead the low-energy velocity planning in Section III. We derive the minimum-energy velocity for a given EV and demonstrate its fundamental difference between that of ICEV.

In this paper, we derive an analytical EV power model with a scale of production EVs such as GM Bolt. We introduce new performance metrics for EV, energy-delay product, energy-square-delay product and energy-cubic-delay product, which demonstrates a practically applicable minimum-energy velocity planning. The proposed method results in up to a 43.4% extended driving range without increasing battery capacity, and a 20.6% improvement of the energy-delay product compared with the best constant-velocity driving.

II. RELATED WORK

The minimum-energy velocity planning is proposed for ICEVS to assist drivers in order to save fuel consumption and reduce emissions [14], [19], [20], [21], [22], [23]. The fuel consumption model is a polynomial form based on a general vehicle dynamics model and takes into account the transmission shift position. A transmission is a mandatory component of ICEVs as the engine torque and power are distinct convex functions of the engine RPM (revolutions per minute.)

There have been previous practices that demonstrate how EVs should change the vehicle velocity to reduce energy consumption under a given road and traffic conditions. Such work commonly formulates an offline optimization problem and uses a dynamic programming (DP) to derive the globally optimal solution [16], [18], [24], [25]. However, once again, the EV power model usually comes from the vehicle physics model only. It borrows the parameters from commercial vehicles such as the vehicle curb weight, aerodynamic resistance from the vehicle specifications and the rolling resistance from the tire specifications [16]. However, this approach is not able to attempt EV-specific low-energy velocity planning because the physics model cannot count on the powertrain efficiency at all, regardless of ICEV or EV.

Electric motors have a flat torque from zero RPM to the base (rated) RPM. Such advantage enables passenger vehicles not to mandate a transmission as long as there is not significant variation in the payload like a heavy-duty trucks and buses. A higher motor revolution speed over the base speed is achieved by the use of field weakening, and a single reduction ratio gear box can exhibit a fast enough top velocity. Regenerative braking is another advantage of EVs, which fundamentally changes the vehicle power model when it decelerates.

An empirical modeling has a potential to achieve more accurate power model of a particular target EV. Related work

fabricates a custom EV, collects the GPS tracking, battery voltage and battery current and constructs an EV power consumption model with several parameters [18]. However, this power model still has important parameters missing that significantly affect the model fidelity such as friction loss, iron loss and windage loss in the motor, loss in the drivetrain and regenerative braking. Inaccurate EV power consumption model misleads the minimum-energy velocity planning. A more recent work fabricates a low-speed custom EV and derived an accurate power model. The power model reflects various EV-specific factors including regenerative braking and even for drivetrain loss by regression analysis of large amount of driving data. However, the power model is limited to low-speed EVs and hard to accommodate production EVs [1]. Some work attempts to accommodate more realistic driving conditions such as traffic signals and stop signs. However, the results are lack of practicality due to the assumption of a constant road slope and a constant cruising velocity with highly simplified EV power models [15], [26], [17].

III. VEHICLE POWER AND ENERGY CONSUMPTION ANALYSIS

A. The minimum-energy cruising velocity

A commonly used vehicle power consumption model is from the vehicle dynamics equation (1). This model considers the traction force only assuming a 100% efficiency of the powertrain (engines, electric motors or both.) Therefore, this model is applicable to any sort of vehicles but not able to explain EV-specific power consumption.

$$P_{trac} = F \frac{ds}{dt} = Fv = (F_R + F_A + F_G + F_I + F_B)v \quad (1)$$

where F_R , F_A , F_G , F_I , and F_B denote the rolling resistance, aerodynamic resistance, gradient resistance, inertia resistance, and brake force provided by hydraulic brakes, respectively [27]. Aerodynamic resistance can be ignored when the vehicle velocity is slower than 40 km/h.

The actual power consumption evaluation of ICEV, i.e., fuel consumption rate, should take into account the powertrain efficiency. A simplified model of ICEV fuel consumption in [19] is written as follows:

$$P_{ICEV} = \frac{P_{trac} + P_{start}}{\eta_{ICEV}} \quad (2)$$

where P_{start} is power consumption of the engine during idling. The engine efficiency, η_{ICEV} , is determined by the gear ratio, engine speed and engine torque. The gear ratio generally dynamically changes by transmission shift. The engine efficiency is generally not simple enough to explain by analytic functions and often described as efficiency maps [19].

Adding a traction motor power model in (2) makes (1) and (2) reflect more realistic EV-specific power consumption characteristics.

$$P_{EV} = \frac{P_{trac}}{\eta_{EV}} \quad (3)$$

$$\eta_{EV} = \frac{P_{trac}}{P_{trac} + k_c T^2 + k_t \omega + k_w \omega^3 + C}$$

where k_c , T , k_i , ω , k_w , C represent a copper loss coefficient, a motor torque, a coefficient by iron and friction loss, an angular speed, a windage coefficient, and constant loss, respectively [1].

EVs mostly use regenerative braking during deceleration, which converts kinetic energy to electric energy except low-cost golf carts. The harvested energy from regenerative braking is closely related to the electromagnetic flux inside of the motor, and the flux is proportional to the motor RPM. The regenerative braking model of an EV can be simplified as (4)

$$P_{regen} = \delta T v + \epsilon \quad (4)$$

where δ and ϵ are regenerative braking coefficients.

The power consumption model (3) is commonly used in various analytical EV power managements [18], [26], [28]. However, there are still considerable sources of power loss from the drivetrain. To make a long story short, (1) – (3) do not accurately explain EV-specific power consumption in various driving conditions according to our intensive measurement with real EVs.

In this paper, therefore, we construct a new EV power model. We borrow the EV-specific power modeling method considering the loss in EV drivetrain using a multivariable regression method from the measured power data and achieve a polynomial fitting [1]. However, we cannot directly use this power model because the model covers only low-speed EVs, i.e., slower than 35 km/h. Thus, we derive our own model coefficients in this paper.

$$P_{EV-specific} = \frac{P_{trac}}{\eta_{EV-specific}} \quad (5)$$

$$\eta_{EV-specific} = \frac{P_{trac}}{P_{trac} + C_0 + C_1 v + C_2 v^2 + C_3 T^2}$$

where C_0 , C_1 , C_2 , and C_3 mean coefficients for constant loss, iron and friction losses, drivetrain loss, and copper loss, respectively. Even if (5) has the same form as (3), the actual coefficients become different if it reflects the characteristics of electric powertrain.

ADVISOR is a vehicle simulator that takes into account various factors of vehicles including engines, electric traction motors, types of drivetrains, shape of chassis, etc. [29]. ADVISOR is a sort of a fast vehicle simulator. It simulates a 700 second vehicle driving in one second. However, because DP is often used to optimize the velocity planning of vehicles [16], [18], [30], such computation time is still hard to accommodate runtime optimization. The DP optimization repeatedly computes the vehicle energy in each distance, velocity and acceleration step. So, it is not proper to run ADVISOR in the inner loop of the DP optimization. For instance, it takes 15 minutes of computation to derive a 10 minute driving velocity planning profile with a 30-step velocity resolution. This is absolutely not acceptable for online recomputation that can be caused by unexpected interrupts while driving. So, instead of using ADVISOR for the speed optimization, we use ADVISOR for the model coefficient extraction. In other words, we use the same form of polynomial as (5) but derive the coefficients by running an EV simulator, ADVISOR.

We choose GM Bolt (1616 kg curb weight) for the target vehicle, but our method does not restrict a particular type of vehicles. The GM Bolt velocity is up to 150 km/h, and it is capable of achieving a 6.5 second 0–100 km/h time with a 150 kW electric permanent magnet motor [31]. This EV is equipped with a 350 V and 57.4 kWh lithium-ion battery pack with 96 groups in series of three 3.65 V cells in parallel [32].

We first implement a GM Bolt vehicle simulation model on ADVISOR based on the vehicle specifications described above and GM Bolt driving experiments for vehicle performance and range at various constant velocities [33], [34], [35], [36]. Then, we extract the model coefficients of (5) by running ADVISOR with the target vehicle specifications. The model coefficient extraction result shows as in Figure 1. The normalized root-mean-square deviation is 5.1%.

B. Energy consumption comparison between ICEV and EV

We compare power consumption behavior of EV and ICEV in this section. As most previous fuel economy analysis work is done by energy (fuel) consumption, we compare energy consumption instead of power consumption for easy comparison.

Figure 2(a) shows the fuel economy (range with a liter of fuel energy) versus ICEV velocity on various road slopes [37]. Red stars denote the minimum-energy driving velocity by the average road slope. The minimum-energy velocity is reduced as the road slope increases. For example, the vehicle has the highest fuel economy at 90 km/h on a -6 degree road slope and 40 km/h on a 2 degree road slope. Fuel economy on a downhill (negative road slope) is not meaningful due to "fuel cut" of modern ICEVs. Compared with the flat road (zero degree), we see the fuel economy drops if the road slope is steeper than 2 degree due to gear shift down.

Figure 2 demonstrates a very interesting EV-specific energy behavior such that the minimum-energy velocity increases as the road slope increases. Such energy behavior is completely opposite to that of ICEV. The efficiency maps of an engine and an electric motor (Figure 3) show that the motor exhibits the maximum torque over the wide range of RPM while the engine exhibits the maximum fuel efficiency only at near 2,000 RPM. Therefore, an engine should be incorporated with a transmission that makes it possible to run the engine at close to the most efficient region, independent to the vehicle velocity. The required engine torque multiplied by the gear ratio (determined by the transmission shift position) also changes by the vehicle gradient resistance (road slope.) The optimal transmission shift position and the minimum-energy velocity are thus determined by the road slope.

On the other hand, a fixed single ratio gearbox (reducer) is generally sufficient for EV since electric motors obtain the maximum torque over the wide range of RPM. The minimum-energy velocity is solely determined by the motor efficiency,

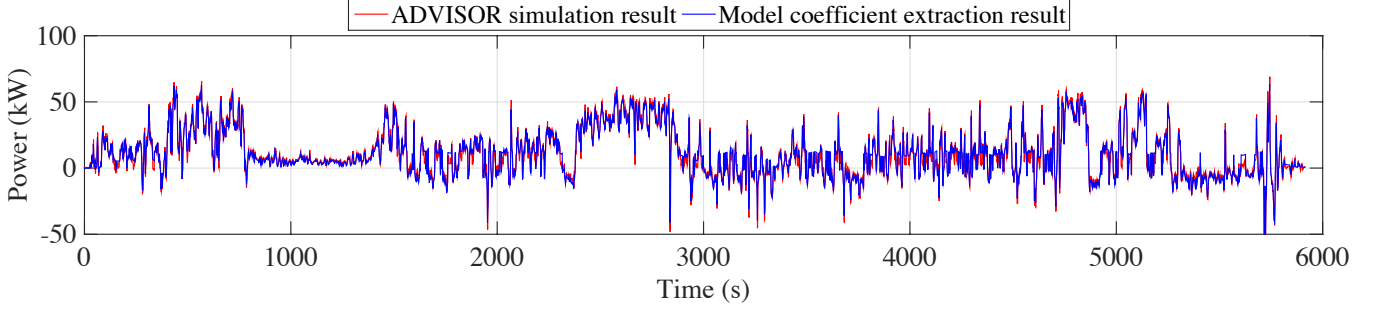


Fig. 1. Validation of the model coefficient extraction.

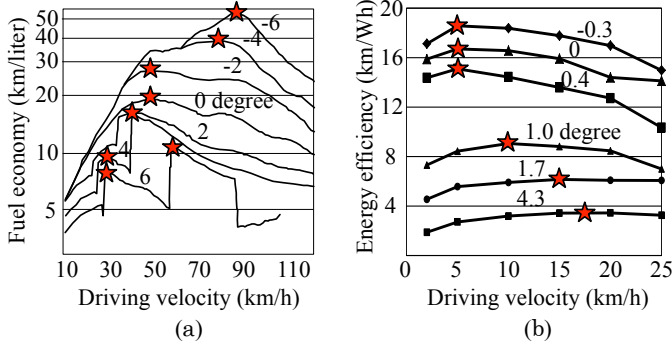


Fig. 2. (a) Fuel economy of a Ford Escort [37] and (b) energy consumption of a custom EV [2] on various road slopes and vehicle velocities.

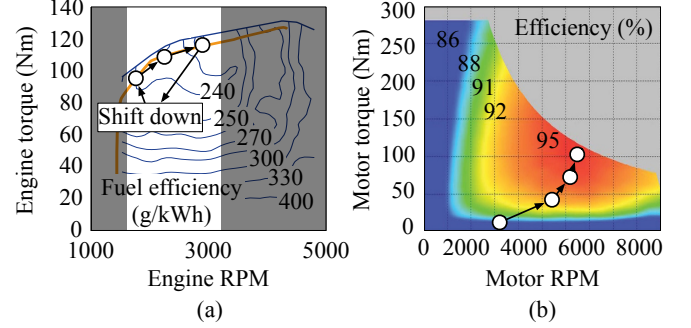


Fig. 3. Efficiency maps of (a) the GM 1.4 liter Voltec engine and (b) the Nissan Leaf 80 kW electric motor.

which is a function of the torque and RPM.

$$\begin{aligned}
 E_{EV} &= \int_{T_{drive}} P_{EV}(v_{const}) dt \\
 &= \frac{P_{trac}}{\eta_{EV}(T, \omega)} \int_{T_{drive}} dt \\
 &= \frac{F_{trac} \times v_{const}}{\eta_{EV}(T, \omega)} T_{drive} = \frac{F_{trac} \times D_{drive}}{\eta_{EV}(T, \omega)}
 \end{aligned}$$

where T_{drive} , V_{const} and D_{drive} denote the driving time, constant velocity and driving distance, respectively. Energy consumption, E_{EV} , with a constant velocity on a given road slope is solely determined by the motor efficiency, η_{EV} .

As the road slope becomes higher, the motor RPM would better be increased to achieve a higher motor efficiency according to the motor efficiency map in Figure 3(b). The minimum-energy velocity of EV increases as the RPM increases because of the fixed single ratio gearbox. It is not possible to derive the minimum-energy velocity for EVs by applying the minimum-energy velocity for ICEVs because of such discrepancies in the powertrains.

IV. FRAMEWORK FOR MINIMUM-ENERGY VELOCITY PLANNING

A. Constant-velocity driving

A constant-velocity driving is not always impractical and actually useful to insure a steady traffic flow and safety. Drivers often drive their vehicles up to the speed limit or slightly over the speed limit following the flow mainly aiming

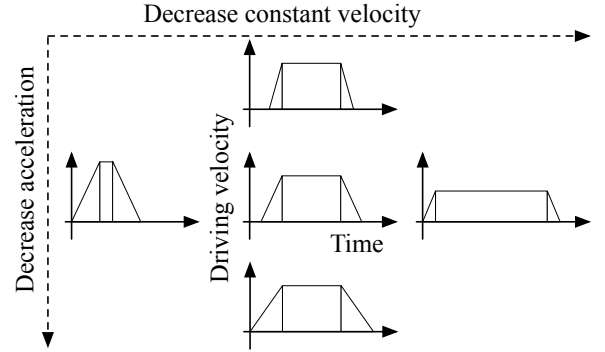


Fig. 4. Various constant velocity and acceleration cases for the same distance.

at shortest possible driving time. However, when it comes to the minimum-energy velocity planning, a constant-velocity driving should use the minimum-energy velocity.

We demonstrate how the cruising velocity, acceleration and deceleration affect EV energy consumption. We perform a design space exploration (DSE) for all feasible vehicle velocities and the acceleration pairs. We obtain the minimum-energy velocity and the initial and final acceleration for a given driving distance as shown in Figure 4. The results of DSE on a flat surface (0 degree road slope) and 4 degree road slope are shown in Figure 5(a) and Figure 5(b), respectively. The point at the minimum battery energy per distance (Wh/km) represents the best constant-velocity driving. Surprisingly, the same distance driving requires significantly different amount of energy by the cruising velocity and acceleration as shown



Fig. 5. DSE of the best constant-velocity driving on (a) 0 road slope and (b) 4 road slope.

TABLE I
ROAD BENCHMARKS.

Road index (#)	Road slope (degree)		
	Minimum	Maximum	Average
1	-3.0	3.0	0.0
2	-4.6	6.7	0.5
3	-5.1	5.1	0.0
4	0.0	3.0	0.8
5	0.0	7.6	3.0

in Figure 4. The energy consumption by the cruising velocity and acceleration pairs also completely changes by the road slopes. These examples indeed show a great potential to save energy consumption of EV with the proposed minimum-energy velocity planning.

B. The minimum-energy velocity planning

In this subsection, we introduce a generalized minimum-energy velocity planning for EV on a road with variable slopes. We construct a DP to find the minimum-energy velocity over distance. The DP obtains a set of the minimum-energy velocity values for every distance step. In Figure 6, the X-axis and Y-axis denote the driving distance from the starting point and the

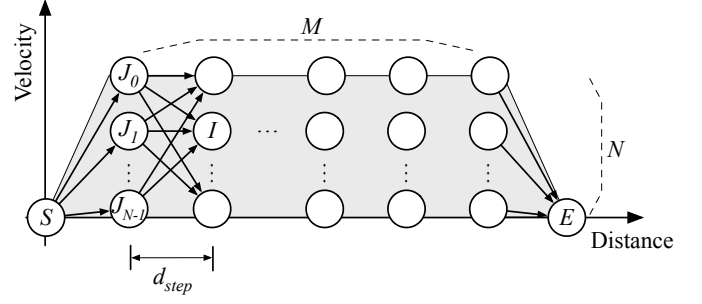


Fig. 6. Problem formulation to explore the minimum-energy velocity planning.

driving velocity, respectively. Each node indicates the driving velocity at a given distance, and an edge between two nodes implies acceleration or deceleration during the distance step (d_{step}). The maximum velocity is v_{max} , and the velocity step between two nodes at the same distance is v_{step} . The number of the nodes in each distance step is $N = v_{max}/v_{step}$, and the number of edges for a distance step is N^2 . One node has N edges going to the next distance, and a node receives N edges. For example, a set of previous nodes, J_0, J_1, \dots, J_{N-1} , goes to the next distance node (Node I). As total number of steps to the endpoint is $M = (\text{driving distance})/d_{step}$, total number of nodes and edges are MN and MN^2 , respectively. There are only two nodes indicating 0 m/s at the starting point (Node S) and endpoint (Node E). A solution of the problem is a sequence of a node selection every distance step from Node S to Node E . The objective and the constraints are defined as

$$\text{Min} \sum_{d=1}^M \sum_{v=1}^N \left\{ \Delta t \frac{x(d, v)P_{d, v} + x(d-1, v)P_{d-1, v}}{2} \right\} \quad (6)$$

$$\text{Subject to} \sum_{v=1}^N x(d, v) = 1 \quad \text{where} \quad x(d, v) = \{0, 1\} \quad \forall d, v$$

where Δt is a time to pass a distance step with a given velocity v , d is a distance from the starting point and $P_{d, v}$ is a power consumption for a node with d and v . Δt varies by the driving velocity and acceleration. $x(d, v)$ is set to 1 if a node at a distance d and a velocity v is selected.

We compare the simulation results between the best constant-velocity driving and minimum-energy velocity planning. Figure 7(a) shows the benchmark road including from -4.5 to 6.7 degree road slopes. From Figure 7(b) to Figure 7(d) show the minimum-energy velocity planning, power consumptions and cumulative energy consumptions, respectively. The best constant velocity is too slow to apply in real cases. The minimum-energy velocity planning guides to speed up the vehicle before entering an uphill. As a result, the EV consumes less energy consumption compared with the best constant-velocity driving at the top elevation. The minimum-energy velocity planning also reclaims more energy from the regenerative braking when the EV finishes the drive. The extended range by the minimum-energy velocity planning is 33.2% with the same battery capacity.

We summarize the comparison of the driving range and driving time on the six benchmarking roads in Figure 8. The six

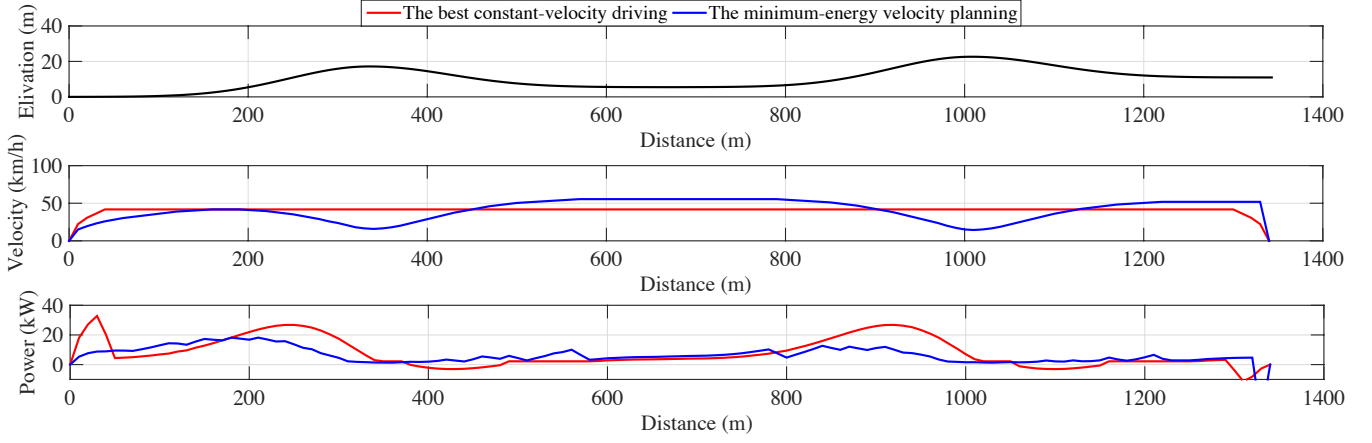


Fig. 7. Results of the minimum-energy velocity planning.

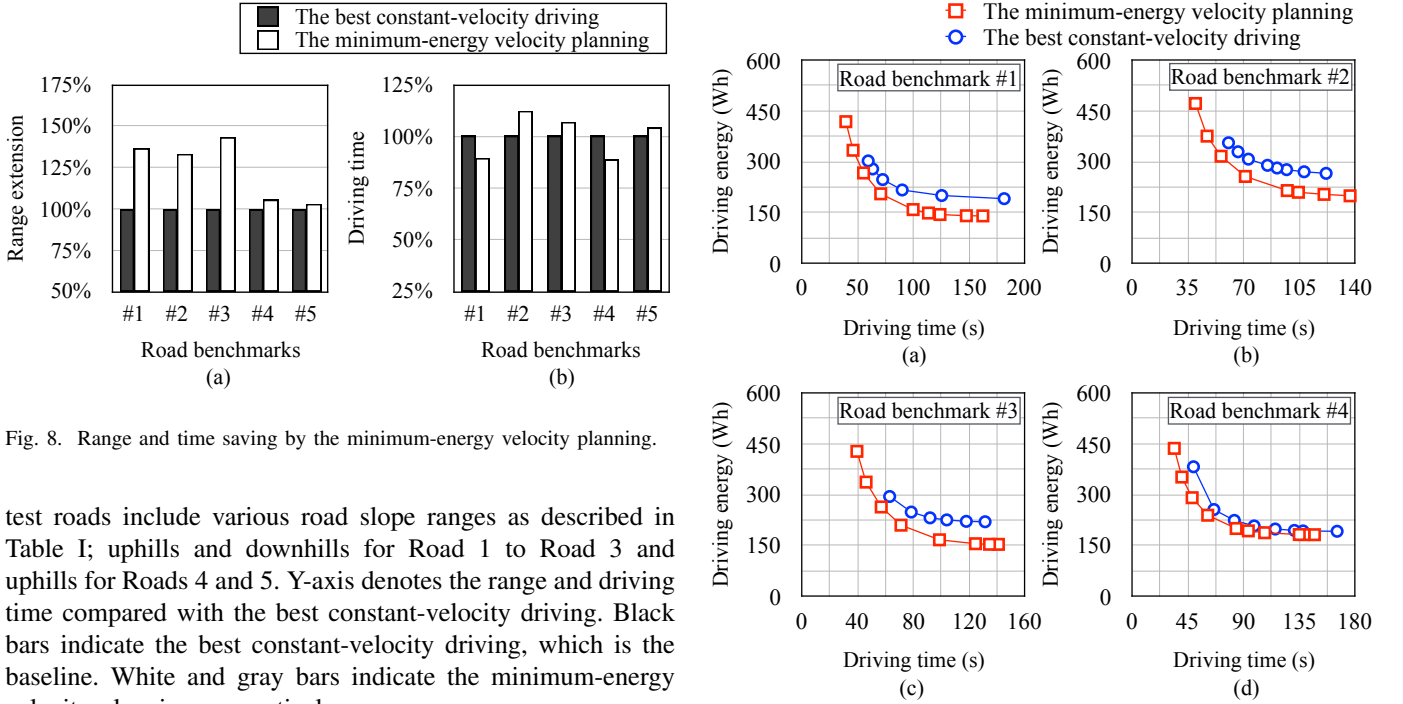


Fig. 8. Range and time saving by the minimum-energy velocity planning.

test roads include various road slope ranges as described in Table I; uphill and downhill for Road 1 to Road 3 and uphill for Roads 4 and 5. Y-axis denotes the range and driving time compared with the best constant-velocity driving. Black bars indicate the best constant-velocity driving, which is the baseline. White and gray bars indicate the minimum-energy velocity planning, respectively.

The range extension is from 2.7% up to 43.4%. The minimum-energy velocity planning extends the range for Roads 1, 2 and 3 by increasing velocities before entering steep uphill, which achieves a shorter driving time than that of the best constant-velocity driving for Road 1. We assume the EV should not drive too slow just for energy saving in order not to bother traffic (10 km/h). We also enforce the minimum acceleration as $0.4m/s^2$. So, we enforce the minimum velocity constraint in the entire optimization process. Range extension for Roads 4 and 5 are relatively smaller than that in Roads 1, 2 and 3 because the velocity is bounded by the minimum velocity constraint while driving on less steep roads i.e., the minimum-energy velocity is lower than the minimum velocity constraint.

V. ENERGY-DELAY CONSIDERATION

The energy-delay curves show the merit of the proposed velocity planning compared with the best constant-velocity driving

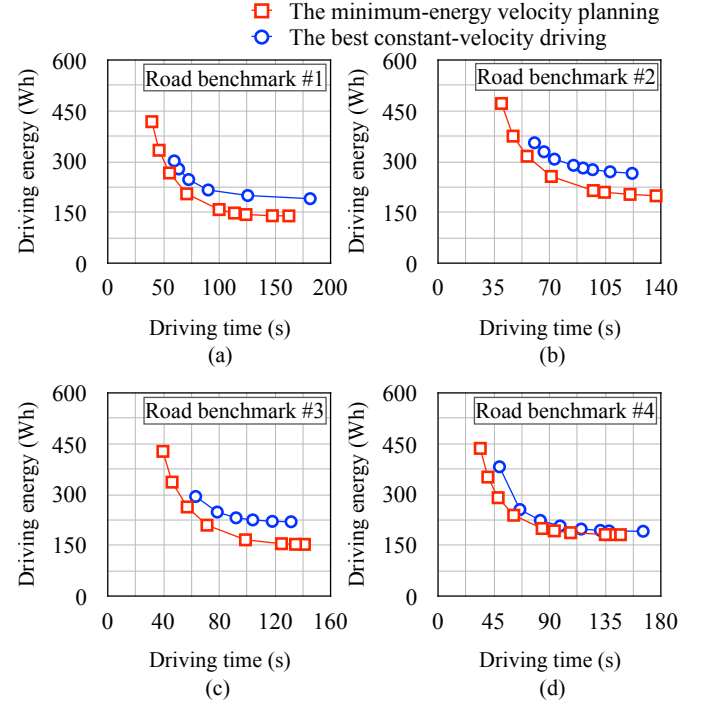


Fig. 9. Energy-delay curves in road benchmarks.

with a deadline. We plot the relationship between driving energy and driving time with deadline constraints in Fig. 9. X-axis and y-axis denote the EV driving time and energy under given deadlines, respectively. The energy-delay plot is useful to figure out the Pareto optimal velocity profiles. The energy-delay curves of the minimum-energy velocity planning are located under the best constant-velocity driving curves, which implies that the minimum-energy velocity planning is better than that of the best constant-velocity driving in terms of energy consumption under the same deadline. The same is true for the driving time under the same energy budget.

However, it is hard to compromise energy and driving time in general. In this paper, we propose to use energy-delay product (EDP), energy-square-delay product (E^2DP), or energy-cubic-

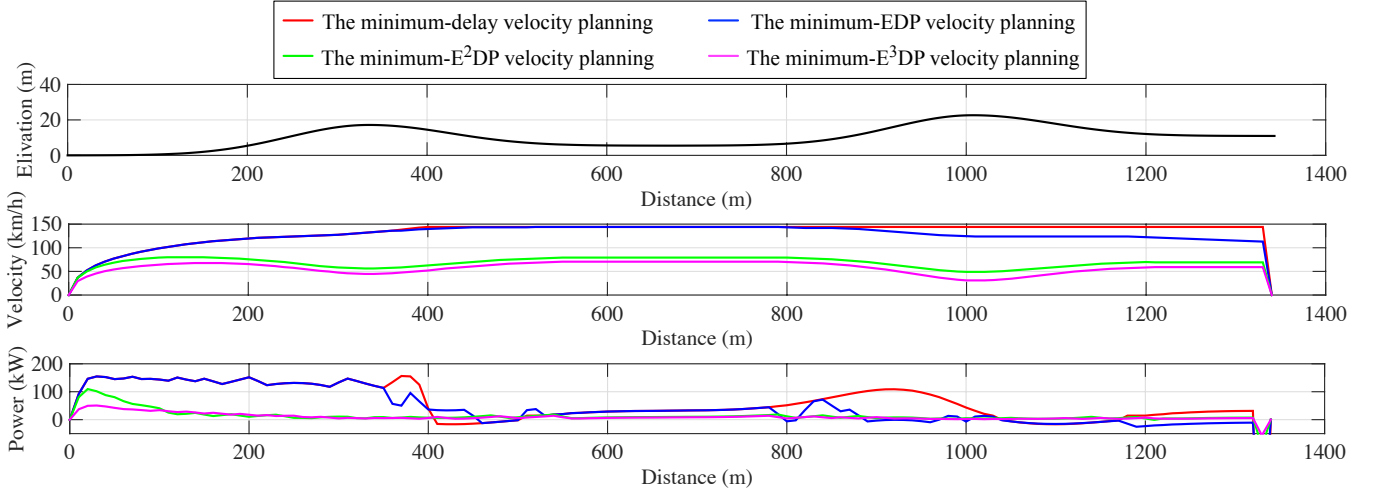


Fig. 10. Velocity profile comparison with optimization of delay, EDP , E^2DP , and E^3DP .

delay product (E^3DP) so that a single metric can consider both energy and driving time. Figure 10 shows the minimum-EDP velocity planning.

If energy delay product (EDP) is used as a cost function, the optimization considers both energy and delay penalty. However, the minimum-EDP velocity planning often overrides the minimum-energy velocity because the delay penalty due to the reduced velocity is greater than the energy penalty due to the increased torque. Therefore, this policy can be used when the deadline is tight.

On the other hand, when the square of energy delay product (E^2DP) is used as a metric to optimize, the energy penalty contributes more to the cost function. As a result, the driving velocity decreases when driving on an uphill because the energy penalty due to the increased torque is greater than the delay penalty as shown in Figure 10. Also, the vehicle velocity on a downhill or a flat road becomes slower than the maximum velocity since the energy penalty due to drivetrain loss is higher than the delay penalty at a high velocity. Therefore, we adopt E^2DP for the performance metric to consider both energy and driving time.

When it comes to energy-cubic-delay product (E^3DP), the effect of energy penalty becomes even more distinct, the average driving velocity becomes lower, and the energy consumption is reduced thanks to regenerative braking. The E^3DP metric can be a proper optimization metric when the battery state of charge is less than 30% for example.

If the deadline is moderate, we use E^2DP for the metric. The EV accelerates to the minimum-energy velocity (or the minimum velocity constraint, whichever comes first) by the road slope and decelerates at the top of the first hill. Then, the EV drives faster than the minimum-energy velocity on the downhill followed by a flat road, in preparation for the next hill. Although the minimum-energy velocity on an uphill is higher than that on a flat road, climbing an uphill consumes more energy. So, the EV gradually loses the velocity while it climbs up on an uphill spending less motor torque, which significantly saves energy consumption.

Chances of energy saving by the minimum-energy velocity planning decrease as the deadline becomes tighter. The velocity planning attempts to reduce driving time with a constant velocity rather than deceleration at the top of the hill. So, if the deadline is tight, we use EDP for the metric. The EV similarly accelerates to the minimum-energy velocity (or the minimum velocity constraint, whichever comes first) by the road slope. However, it does not decelerate at the top of the hill to reduce driving time. It also does not slow down when climbing up the second uphill. The EV keeps driving at the same velocity on the downhill and the following flat road until it arrives at the destination.

Figure 11 shows energy-delay product of the best constant-velocity driving and the velocity planning with EDP , E^2DP and E^3DP as a metric on the five road benchmarks. The leftmost bars indicate the constant-velocity driving, which minimizes the energy-delay product not energy consumption in this comparison. The proposed driving planning results in average 9.9% and up to 20.6% improvements of energy-delay product. The improvements occur especially when the slope of the uphill is steep. The driving velocity on a flat road is faster than that of the best constant-velocity driving at the expense of relatively little energy to save driving time. Then, the velocity decreases when climbing the following uphill to spend less motor torque, which saves more energy.

VI. IMPACT OF THE EV POWER MODEL FIDELITY

Lesson learned from embedded systems power management, it is crucial to extract an accurate power model from the device to system. Power optimization results largely change by the power model. Inaccurate power model obviously misleads the power optimization results. It goes without saying that an accurate EV power model mandates for the minimum energy velocity problem that reflects power variation by the velocity, acceleration, road slope, payload, and so forth.

We compare the minimum-energy velocity planning results with i) a lossless vehicle dynamics model (1), ii) a vehicle dynamics model with motor loss (3) and iii) an EV-specific

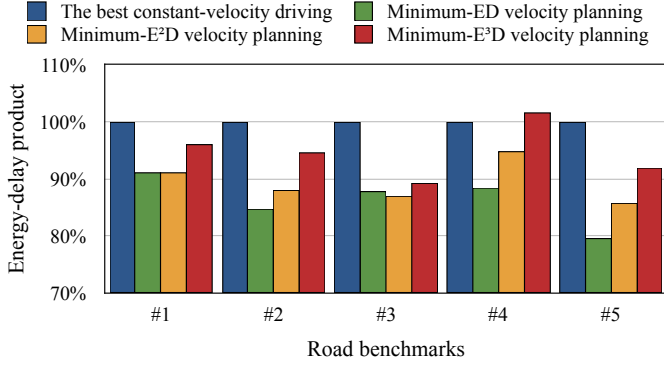


Fig. 11. Energy-delay product comparison.

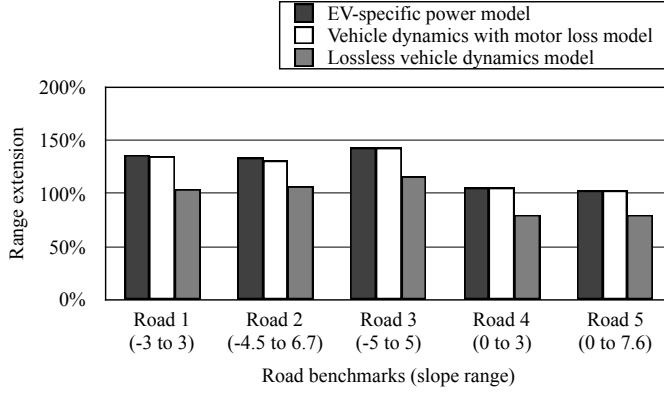


Fig. 12. Range comparison by EV power consumption models.

power model (5) described in Section III-A. Inaccurate EV power consumption model causes suboptimal EV driving optimization.

Figure 12 shows the comparison of range extension by the EV power models. The X-axis indicates the types of benchmark road slopes, and y-axis indicates the range; 100% range implies the range by the best constant-velocity driving. Black bars indicate the range with the lossless vehicle dynamics model, which does not consider motor loss and vehicle power loss at the drivetrain. White and gray bars indicate the range with the vehicle dynamics with motor loss model and the EV-specific power model, respectively.

Driving optimization using more accurate power model shows more extended range. The extended range with the EV-specific power model is average 1.6% and 32.8% compared with the minimum-energy velocity planning with the vehicle dynamics with motor loss model and lossless vehicle dynamics model, respectively. One of main reasons is that the underestimated EV power loss becomes a considerable portion of total energy consumption when the EV drives on low road slope or downhill.

VII. CONCLUSIONS

This paper introduces a novel minimum-energy velocity planning for all-electric vehicles (battery electric vehicles, BEV), which is inspired by low-power scheduling for computing systems. This work is a showcase such that legacy system-level low-power design methodologies significantly improves

electric vehicle fuel efficiency. We demonstrate the potential gain from the proposed minimum-energy velocity planning for EV. We show the importance of EV-specific power model comparing the actual energy gain from EV using different fidelity power models. In addition, this paper is the first to show the difference of the minimum-energy velocity planning between the full electric vehicles and internal combustion engine vehicles. Most importantly, we introduce energy and time combined metrics such as, energy-delay product (EDP), energy-square-delay product (E^2DP) and energy-cubic-delay product (E^3DP) for a tight time deadline constraint, a loose time deadline constraint, and a tight deadline constraint, respectively. The proposed method results in up to a 43.4% extended range and a 20.6% improvement of the energy-delay product compared with the best constant-velocity driving. The minimum-energy velocity planning will become more crucial when full autonomous driving is widely deployed.

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