EVTeC 2023
6th International Electric Vehicle Technology Conference 2023
20231047

Development of predictive SOC Management control for PHEV in cooperation with connected services

- Control architecture and benefit -

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ABSTRACT: This report shows the control algorithm and performance of the Predictive EV Drive and its benefit on fuel efficiency in real life. This control switches over the driving modes automatically depending on road load, battery level and traffic conditions. Furthermore, the application of this control for geo-fencing is also shown in this report. In order to achieve these functions, navigation system and plug-in hybrid control has been newly developed.

KEY WORDS: PHEV, navigation, battery control, driving power, geo-fencing

1. Introduction

In order to contribute to the improvement of real-world fuel efficiency of HEVs and PHEVs towards carbon neutrality, "PED-Predictive Efficient Drive" has been developed. It aims more efficient State Of Charge (SOC) management by predicting driving conditions and driver's behavior in cooperation with connected navigation technology.

Predictive EV Drive predicts traffic conditions and road load towards the destination set by the driver. It formulates a real-time control plan based on the current battery level and switch over between electric and hybrid driving - to improve fuel efficiency. Further explanation is about control architecture and benefit.

2. Predictive EV Drive

2.1 Improvement for current PHEV behavior

In order to use up all the battery energy which is charged by plugging-in, electric driving is performed when such charged power is available. And hybrid driving (with engine support) is automatically performed when the battery energy is low. When engine power output is low in hybrid mode, efficiency is generally low. The engine efficiency is generally better on highways and uphill than in urban areas and traffic jams. Therefore, as an example shown in Fig.1 - current PHEV can be more efficient by driving in hybrid mode at uphill.

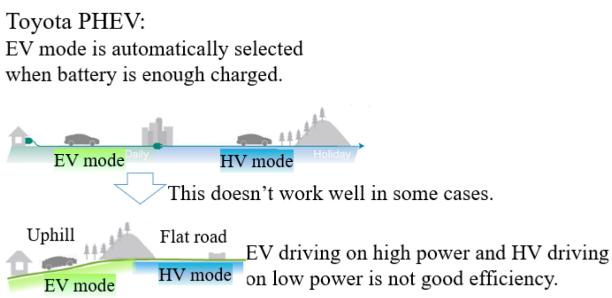


Fig.1: Current Toyota PHEV behavior

2.2 Aim of Predictive EV Drive

To improve the above situation, this control shifts into the hybrid driving in high road load areas (highway, uphill, etc.) and chooses electric driving in low road load areas (urban, traffic jam, etc.) - to improve real world fuel efficiency by optimizing the use of charged battery energy (See Fig.2).

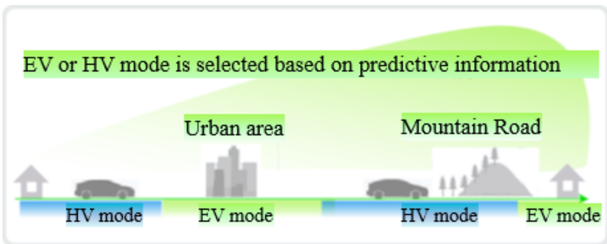


Fig.2: Image of Predictive EV Drive

In order to manage SOC control for the entire route, predicting the route information until destination is necessary. Therefore, this control is activated when route guidance is set in Toyota navigation system.
Fig.3 shows the customer journey with Predictive EV Drive. This control changes the driving mode automatically between EV and HV mode in order to consume all remaining energy in the battery when arriving at the destination.
The result of this control system is displayed at the destination.

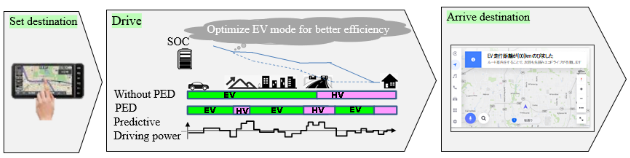


Fig.3: Customer journey with Predictive EV Drive

2.3 Control architecture

The navigation system takes care of calculating road load towards the destination and creates predictive information which can be shared with hybrid ECU.
The hybrid ECU performs vehicle mode planning and execution of control based on the current battery level and available predictive information (See Fig.4).

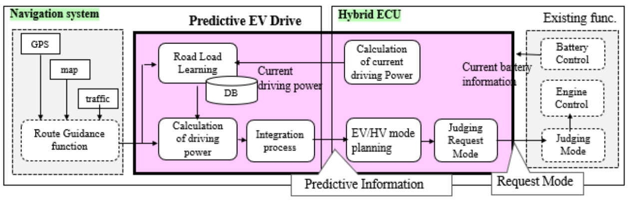


Fig.4: Control architecture

2.4. Generation of predictive information in navigation system

The navigation system generates predictive information that could estimate the energy (Wh) and driving power (kW) along the route ahead, to fulfil the below boundary conditions:

- To use up all battery energy until arriving at the destination
- To switch over to hybrid driving in high road load areas

The route to the destination is divided into several sections (See Fig.5). It predicts driving power (based on road type, traffic conditions, road load), time (based on distance, vehicle speed) and distance for each section.

Following three additional processes are necessary to above basic information, in order to generate accurate predictive information.


Fig.5: Image of predictive information linked to route

(1) Calculation of driving power

Topography and traffic information from route is necessary to predict driving power, if the route has not been traveled before. In such a case, driving power is calculated using gradient information available in the map and vehicle speed coming from live traffic services (see the following equation).

- Driving power[kW]= (Gradient resistance + Driving resistance) ×Estimated Velocity ÷ 3600
- Gradient resistance[N]=Vehicle weight × Estimated slope ×9.8÷ 100
- Driving resistance[N]= RLa × Estimated Velocity ^{2} + RLb ×Estimated Velocity + RLc
- Estimated Velocity[km/h]=Velocity based on road category and from live traffic services
- Estimated slope[%]=Gradient data from Geospatial Information Authority (GSI)

However, the acceleration and deceleration losses cannot be considered since the navigation provided vehicle speed and gradient values are averaged over sections. So, the estimated road load can be different from actual road. Therefore, road load learning function has been implemented in order to improve the accuracy on the roads already travelled.

(2) Road load learning function

In order to adapt to real driving conditions and driving style, the system learns vehicle speed, road load and gradient in sections along the route. Then driving load is calculated by hybrid ECU in real-time. This real-time driving load is transmitted to the navigation system and then linked to the map. The real-time driving load calculation is according to the following formula:

- Driving load [N]
  = Driving force (from engine and motor) × System efficiency

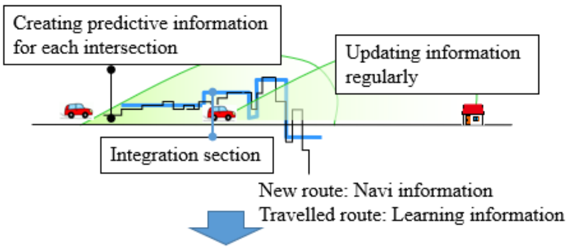
On roads that have been already travelled, this learning information has priority to generate predictive information.

<u>(3) Integration Process</u>

When the destination is at a distant location, the amount of data to handle becomes too large. A typical case is long-distance driving scene as this control supports trips that cannot run only with battery energy.

Therefore, sections next to each other with small road load differences will be combined so they can be easily handled by the hybrid ECU.

Also considering the processing load and communication delay on the hybrid ECU, information from the current vehicle position until a certain distance away is extracted from navigation system at a time and processed at fixed interval along with the latest traffic information. (See Fig. 6)



Section	1	2	3	4	5	6	7	8	9	10	11
Length[m]	300	321	413	352	380	445	390	420	400	510	320
Power[kW]	-1.0	-0.5	-4.5	-2.6	-3.0	2.4	5.2	12.5	11.0	0.5	-0.2
Velocity[km/h]	42	55	57	53	38	62	98	110	122	55	54
Road type	0	0	0	0	0	0	2	2	2	0	0

Fig.6: image of predictive information generation

When the destination is more than certain distance away, hybrid ECU is notified that whole route information is not available. As a result, HV mode is planned to maintain current battery energy regardless of current SOC, until whole route information is available.

2.5. Planning of mode control in hybrid ECU

The hybrid ECU receives the predictive information and makes a mode control plan as follows:

<u>(1) Target area selection of all battery energy consumed (near the destination):</u>

To ensure all battery energy is consumed until arriving at the destination, some area before the destination is excluded from the EV mode control planning since the accuracy of predictive information is limited.

<u>(2) Determine whether vehicle could reach the destination in EV mode:</u>

The control calculates whether the vehicle could reach its destination in only EV driving mode based on current battery energy.

<u>(3) Order of priority for EV mode:</u>

The control prioritizes the EV mode planning in certain areas where electric driving is expected – even though it can be less efficient.

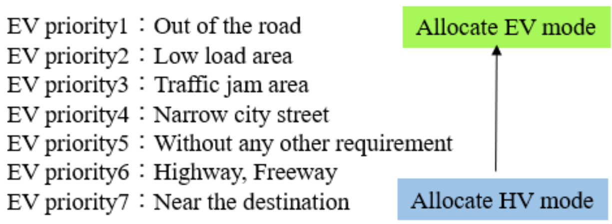


Fig.7: Priority level of the EV mode

<u>(4) EV/HV mode plan for each section:</u>

The control allocates the EV driving mode in descending order of EV priority. When the cumulative energy consumption of the EV mode planned areas exceed current battery energy, control allocates HV mode to remaining area. In case areas have same priority level for EV mode, lower road load area is prioritize to EV mode.

When the destination is more than certain distance away and whole route information is not yet available, step (2) is skipped. And EV priority 6 and 7 in the table 1 is planned as HV mode because battery is supposed to be consumed until arriving at destination.

<u>(5) Final optimization:</u>

In addition to above priorities, final driving mode is determined by consideration of avoiding unnatural behavior due to fluctuations from quick mode changes and to select EV mode for avoiding overflow of battery - in case of downhill with high SOC.

3. Real world evaluation in vehicle

The efficiency of the system was tested and verified in real world on Japanese and European roads with various battery levels and driving lengths.

3.1 Route

The evaluation route selected is as shown in Fig. 8. This route represents various road load conditions such as downhill, uphill and highway. In addition to above route, short-length(~30km), medium-length(~100km) and long-length(~200km) routes has been tested. Since this function will be introduced in Japan and

Europe, real environment test has been performed in Belgium and Germany - to consider European conditions also. Fig.9 shows the route of long length trip in Europe.

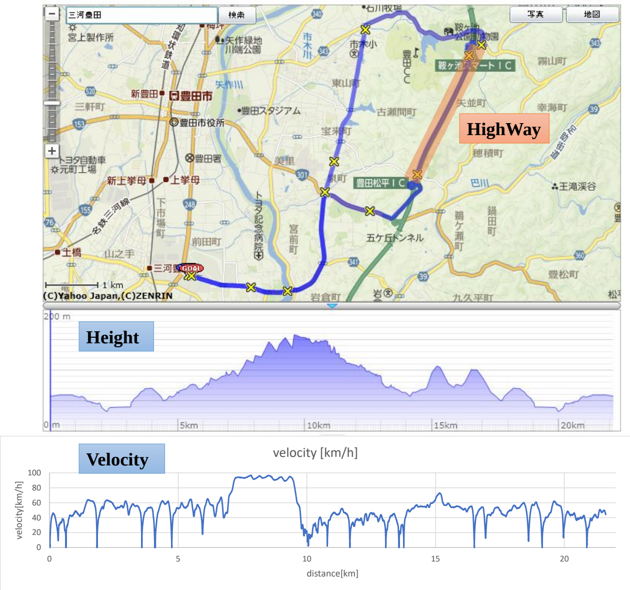


Fig.8: Short Course1@JPN

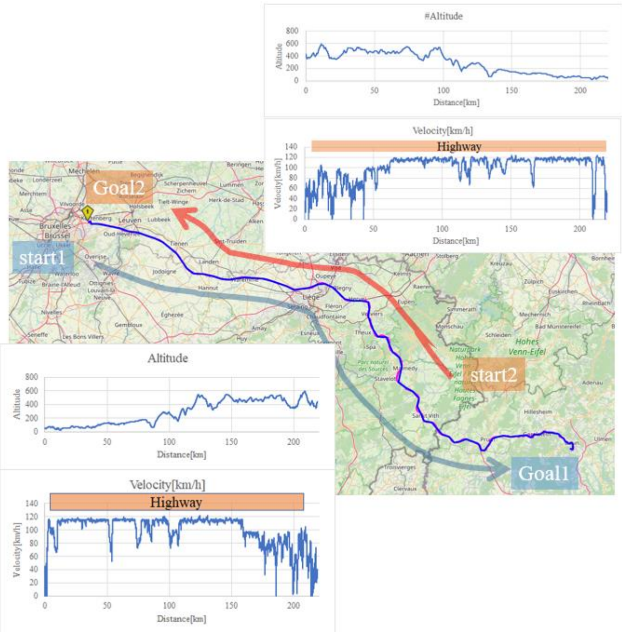


Fig.9: Long Course 2 and Long Course 3 @Euro

3.2 Method to evaluate benefit of the system

The fuel efficiency benefit is calculated by simulation of actual vehicle data (see the Fig.10). The Predictive EV Drive function was active to record vehicle data during driving the routes. The recorded data was used in the simulation to evaluate fuel efficiency with Predictive EV drive ON. To simulate fuel efficiency with this control OFF, only driving pattern from the above recorded data was used.

The reason for choosing this method was to avoid repeatability issue in real world while testing with control ON & OFF.

Input information for the simulation:

・Velocity, road gradient, air conditioning and SOC at start

・ The actual change between EV & HV mode during testing with control ON

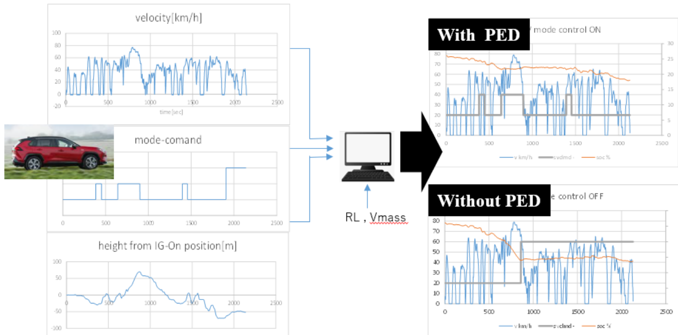


Fig.10: Simulation of fuel efficiency benefit based on the actual vehicle data

3.3 Results

Above procedure has been performed to all routes. Table1 shows the summary of benefit in each route.

Table1: Benefit of Predictive EV Drive in each route

: with Learning data

Course		n	Dist [km]	Initial SOC [%]	Fuel Efficiency[km/l] Off	On	Δ[%]	CO2[g]@JPN Off	On	Δ[%]	CO2[g]@EURO Off	On	Δ[%]
JPN	Short1	1	21.6	26.1	19.91	19.97	0.30	2365.8	2360.3	-0.23	1773.0	1768.0	-0.28
		2	21.6	26.1	20.08	20.33	1.23	2349.2	2331.6	-0.75	1780.1	1765.0	-0.85
		3	21.3	26.1	18.44	18.68	1.30	2574.6	2549.4	-0.98	1997.2	1962.9	-1.71
		4	21.3	25.9	17.37	17.75	2.20	2747.5	2706.6	-1.49	2183.2	2147.9	-1.62
	Short2	1	26.0	26.1	16.91	17.26	2.07	3461.2	3404.5	-1.64	2904.2	2844.1	-2.07
		2	26.0	26.1	17.18	17.41	1.34	3409.4	3372.2	-1.09	2857.7	2816.1	-1.46
		3	26.3	26.2	17.54	17.86	1.82	3329.8	3286.0	-1.31	2758.6	2733.1	-0.92
	Short3	1	26.0	26.1	17.34	17.35	0.06	3369.4	3367.5	-0.06	2814.5	2812.8	-0.06
		2	26.0	25.9	16.71	16.79	0.48	3499.6	3485.0	-0.42	2926.5	2912.0	-0.49
		3	26.0	26.1	17.54	17.70	0.91	3328.5	3306.2	-0.67	2760.5	2744.1	-0.59
	Middle1	1	54.6	26.1	16.93	17.07	0.84	7353.5	7300.0	-0.73	6765.9	6712.6	-0.79
		2	54.6	26.1	16.48	16.63	0.93	7572.3	7509.8	-0.83	6968.4	6906.2	-0.89
		3	54.6	26.1	16.75	16.91	0.99	7436.7	7370.4	-0.89	6846.5	6782.7	-0.93
	Middle2	1	35.3	26.0	17.72	17.73	0.06	4387.6	4386.7	-0.02	3832.7	3830.6	-0.05
		2	35.3	26.0	15.03	15.08	0.39	5325.6	5309.6	-0.30	4748.6	4731.8	-0.35
		3	35.3	26.1	16.26	16.37	0.65	4923.4	4895.1	-0.58	4344.0	4312.7	-0.72
	Long1	1	206.6	80.0	20.73	20.84	0.52	22239.4	22123.0	-0.52	19148.8	19026.7	-0.64
		2	206.6	80.0	20.60	20.88	1.36	22371.5	22129.3	-1.08	19259.4	19027.0	-1.21
		3	206.6	80.0	19.67	20.01	1.74	23421.9	23102.3	-1.36	20310.2	19980.6	-1.62
	Long2	1	207.6	66.0	21.81	21.84	0.18	21493.2	21448.7	-0.21	19062.6	19018.3	-0.23
		2	207.6	66.1	20.55	20.74	0.93	22795.5	22609.4	-0.82	20332.5	20147.3	-0.91
		3	207.5	66.0	22.72	23.00	1.23	20539.4	20324.0	-1.05	18099.8	17881.2	-1.21
Average							**0.98**			**-0.77**			**-0.89**
Course		n	dist[km]	initial SOC[%]	Fuel Efficiency[km/l] Off	On	Δ[%]	CO2[g]@JPN Off	On	Δ[%]	CO2[g]@Euro Off	On	Δ[%]
EURO	Middle1	1	62.2	51.7	14.57	14.87	2.09	10772.0	10598.3	-1.61	8951.6	8777.7	-1.94
		2	70.5	50.9	13.82	14.06	1.77	11370.5	11212.0	-1.39	9594.3	9436.7	-1.64
	Long1	1	127.8	89.0	14.49	14.62	0.93	19342.3	19213.8	-0.66	15841.9	15713.3	-0.81
		2	127.8	89.6	13.98	14.13	1.01	20093.7	19936.0	-0.78	16572.9	16415.1	-0.95
	Long2	1	220.1	89.7	12.97	13.04	0.55	38127.7	37947.3	-0.47	34536.0	34355.6	-0.52
		2	220.2	89.1	13.91	14.13	1.55	35458.2	34986.5	-1.33	31908.0	31445.9	-1.45
		3	220.2	86.9	12.84	12.98	1.09	38584.2	38216.4	-0.95	35130.8	34772.3	-1.02
	Long3	1	221.9	90.3	16.11	16.09	-0.08	30705.0	30749.5	0.15	27106.1	27150.9	0.17
		2	221.3	90.2	15.70	15.64	-0.34	31493.3	31596.2	0.33	27932.4	28035.9	0.37
		3	220	90.7	15.52	15.52	-0.03	31880.0	31920.6	0.13	28292.6	28353.4	0.21
Average							**0.94**			**-0.74**			**-0.85**

*CO_2 is including both CO_2 expelled with gasoline and necessary for power generation of plug-in electricity.

Note) CO_2 intensity of electricity generation(kg-CO_2/kWh) is estimated value by Toyota Motor Corp. for consideration in IEA

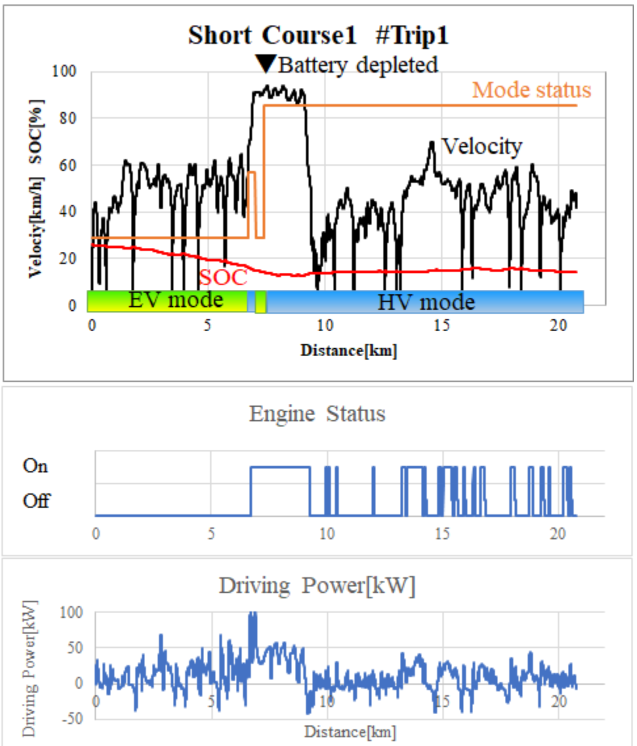
WEO2021, Data Statistics and so on. (This is calculated life cycle factor including upstream emission)

3.4 Observations

<u>(1) Predictive information accuracy</u>

Following case is an example that shows difference in control planning beween first and second trip due to improvement in predictive information accuracy.

Fig.11 shows EV/HV control behavior and trip result using navigation information on short course1. Battery depletion was high in 1st half of the trip and then battery was fully depleted on the highway, before city driving. EV mode was selected for a long time in this 1st half of trip because road load from navigation was assumed less than actual load road.



Fuel Efficiency Δ[%]	CO2 Δ[%] @JPN	CO2 Δ[%] @Euro
0.30	-0.23	-0.28

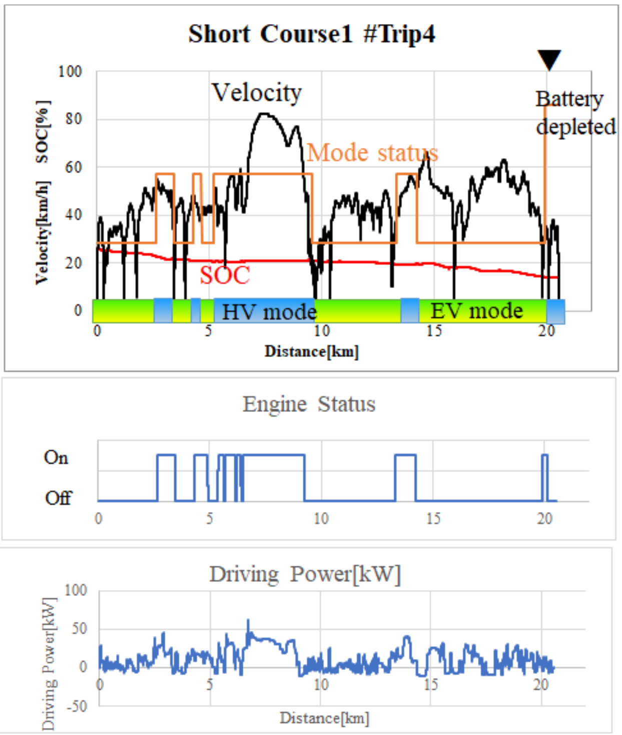
Fig.11: Result of the Short Course1 trip1

Fig.12 shows better control on same route after road load learning. The prediction becomes more accurate on previously travelled roads, thanks to the accumulated route data from the learning system.

If prediction information error is high, it can result in a different battery depletion than original mode plan.

Even without learning data, hybrid-ECU re-calculates the mode plan every 1 minute to minimize the impact of prediction error.

In fact, it is possible that recalculation might not be enough to compensate prediction error.



Fuel Efficiency Δ[%]	CO2 Δ[%] @JPN	CO2 Δ[%] @Euro
2.20	-1.49	-1.62

Fig.12: Result of the Short Course1 trip4

The accuracy of predictive information is analyzed to show the difference between the first trip and repeated trips with learning. Fig.13 shows accumulation of difference between predictive energy consumed and actual energy consumed to compare before and after learning.

In the first trip, actual energy tends to be larger than predictive energy from navigation map. In this case, it shows 89Wh/km difference. On the contrary, repeated trips show only up to 22Wh/km difference - thanks to the learning system. Graph on right hand side in Fig.13 shows the variation of actual vehicle energy consumption during each trip. Generally, real testing environment has variation due to traffic, environment, etc. These tests have up to 17Wh/km variation. Therefore, we can conclude benefit of learning system from these results.

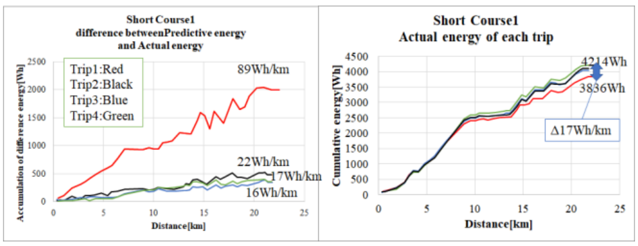


Fig.13: Short Course1 accuracy of Predictive info.

Table2 shows error due to predictive information accuracy with other routes. It is evident that improvement from learning system is observed in other routes as well.

Table2: Predictive information error

Country	JPN						Euro			
Course	Short1	Short2	Short3	Middle1	Long1	Long2	Middle	Long1	Long2	Long3
n1_map	89	77	74	71.5	32.8	43	-22.3	20.2	74.7	38.7
n2	16	5.1	-12.1	5.9	3.7	14.9	-5.6	1.7	-11.6	-1.4
n3	17	5.6	-2.5	-6.4	17.7	-9			14.0	12.0

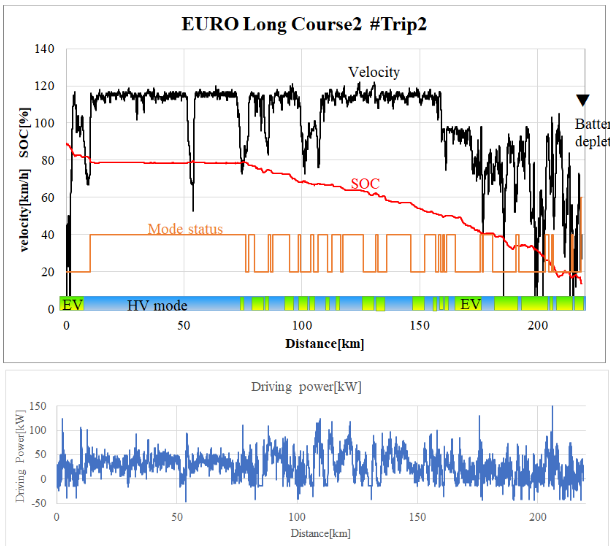
Table3 shows average of fuel efficiency and CO_2 results for all routes before and after learning.

Table3: Result of the before and after learning

	Fuel Efficiency Δ[%]	CO2 Δ[%] @JPN	CO2 Δ[%] @Euro
n1	0.68	-0.55	-0.66
n2,n3	1.07	-0.84	-0.95

(2) Long trip data result

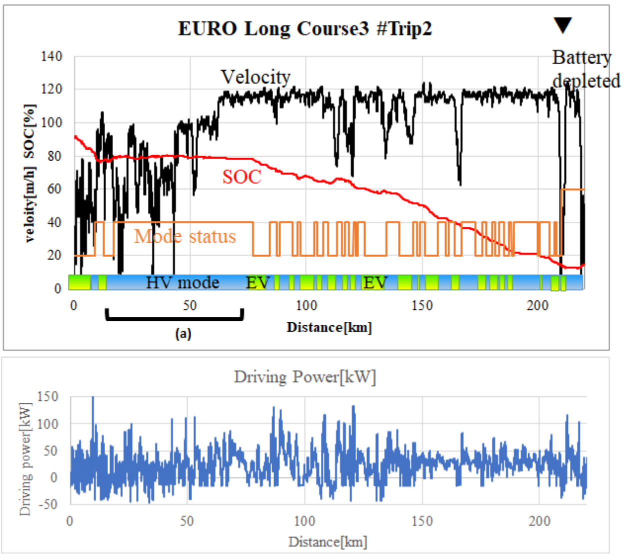
Fig.14 shows long course 2 and 3 in the Europe. Route information is shown in Fig9.



Fuel Efficiency Δ[%]	CO2 Δ[%] @JPN	CO2 Δ[%] @Euro
1.55	-1.33	-1.45

Fig.14: Result of the Long Course 2

When destination is more than certain distance away, predictive information for whole route is not available at the beginning of the trip. HV mode is typically planned until whole route information is available. Fig 14 shows good result because highway driving is in 1st half of the trip which is planned as HV. On the contrary, Fig.15 shows not ideal scenario because city driving is in 1st half of the trip which is planned as HV(Fig.15(a)). Therefore, EV is selected during highway driving after whole route information is available. This issue is due to ECU capability limitation, which will be improved in future.



Fuel Efficiency Δ[%]	CO2 Δ[%] @JPN	CO2 Δ[%] @Euro
-0.34	0.33	0.37

Fig.15: Result of the Long Course 3

4. Application for geo-fencing

4.1. Expanding on predictive EV Drive function

In Europe, geo-fencing is coming under the spotlight for encouraging PHEV customers to drive more electric in city areas. Some other competitors have already implemented geo-fencing system for their PHEV in specific areas to encourage drivers to switch over into EV driving mode. (See Fig.16)

Fig.16: Geo-fencing image (PHEV)

The Predictive EV Drive is originally designed to drive in EV mode by considering the total route, but it can also support geo-fencing requirement by adding information about specific geo-fencing areas and promote driving as EV. (See Fig.17)

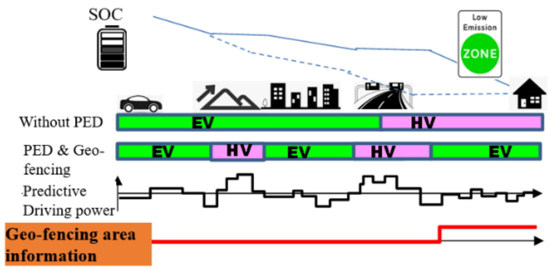


Fig.17: Image of application of Predictive EV Drive for geo-fencing

Fig.18 shows control architecture of Predictive EV Drive for geo-fencing. Geo-fencing functions are implemented over the Predictive EV Drive.

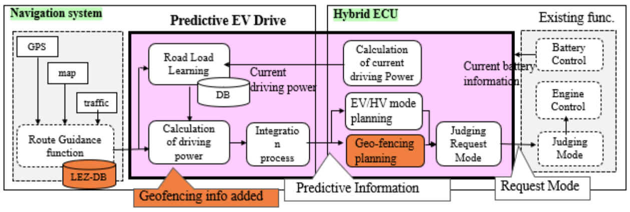


Fig.18: Control architecture of Predictive EV Drive for geo-fencing

To ensure that the benefits from Predictive EV Drive are kept even with geo-fencing feature, a new control considering geo-fencing is added dedicated to EV/HV mode planning.

Geo-fencing feature is implemented in addition to the original vehicle mode control that manages switching between EV and HV mode.

Geo-fencing area information which prioritizes EV mode is implemented in the navigation. This information is sent to hybrid ECU to be combined with other section information.

Geo-fencing planning in hybrid ECU is the new function to realize EV mode in the geo-fencing area.

EV/HV mode planning control calculates energy demand to achieve EV mode in whole geo-fencing area. When battery energy is not enough, HV mode is requested to reserve battery energy before entering geo-fencing area. Conventional predictive EV/HV switching mode control is also working in parallel to achieve both - fuel efficiency benefit and geo-fencing function.

Fig.19 is the case that combines both functions.

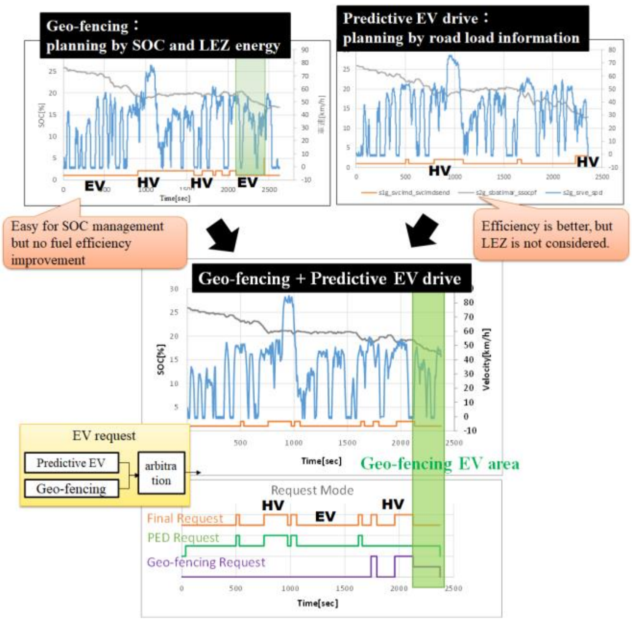


Fig.19: Image of vehicle mode control including geofencing

4.2. Method to evaluate benefit of geo-fencing function

There are 2 main concerns when practically implementing geo-fencing function.

First concern is how to estimate the battery energy consumption to drive as EV since predictive information is not perfectly matching with actual driving condition.

Second concern is to ensure that battery energy is consumed as much as possible at destination - to achieve good CO_2 results.

Therefore, calibration of battery energy margin before destination has been optimized to address these two concerns. Fig. 20 shows two example of geo-fencing driving scenarios.

If SOC depletes less than predicted, battery energy is able to be consumed after geo-fencing area to optimize better CO_2. If SOC depletes more than predicted, battery energy is used for geo-fencing function is stead of later EV. Therefore Case (b) which has geo-fencing area at the end of trip is more severe than other Case (a).

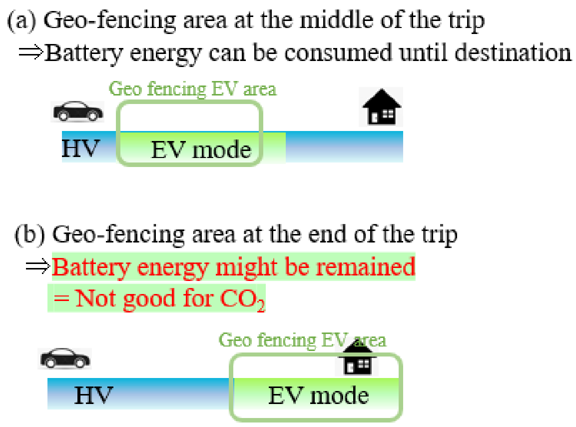


Fig.20: Geo-fencing driving case

Therefore, geo-fencing at the end of trip is set for each course in Japan and evaluated.

4.3. Results of Predictive EV Drive for geo-fencing

Since geo-fencing regulation is not fixed yet, this evaluation allows engine starting in the geo-fencing area if battery energy is depleted before destination. EV driving distance ratio, EV driving time ratio, fuel efficiency and CO_2 benefit is evaluated with these routes.

Table4 shows the results of geo-fencing function from real world evaluation with the actual vehicle.

Table4: Benefit of the control in each route

■ : Battery depleted before reaching the destination in geo-fencing area

EV area [km]	Course	no	dist [km]	initialSOC [%]	Fuel Efficiency[km/l]			CO2[g]@JPN			CO2[g]@Euro		
					Off	On	Δ[%]	Off	On	Δ[%]	Off	On	Δ[%]
2.0	Short1	1	21.6	25.9	21.31	21.86	2.60	1946.7	1941.6	-0.26	1627.5	1649.5	1.35
		2	21.6	26	20.26	20.85	2.91	2360.5	2323.4	-1.57	1800.4	1843.0	2.37
		3	21.6	26	20.95	21.40	2.16	2274.8	2249.8	-1.10	1699.5	1752.3	3.11
	Short2	1	26.6	26	20.39	20.63	1.20	2918.7	2887.7	-1.06	2375.0	2344.0	-1.31
		2	26.6	26	18.56	18.84	1.50	3209.7	3174.2	-1.11	2646.7	2660.0	0.50
		3	26.6	26	19.16	19.43	1.40	3107.6	3081.1	-0.85	2536.8	2583.8	1.85
	Short3	1	26.3	25.9	20.29	20.43	0.67	2896.6	2893.8	-0.10	2317.1	2396.0	3.41
		2	26.3	26.1	19.25	19.47	1.11	3058.1	3042.3	-0.52	2468.4	2536.5	2.76
		3	26.3	26	19.63	19.77	0.70	3001.1	3001.6	0.02	2442.8	2569.6	5.19
7.0	Middle1	1	54.5	26.1	21.26	21.56	1.41	5824.6	5754.0	-1.21	5227.4	5182.1	-0.87
		2	54.6	26.1	22.63	23.01	1.69	5471.4	5396.8	-1.36	4883.5	4865.0	-0.38
		3	54.6	26.0	23.57	24.06	2.09	5239.7	5155.4	-1.61	4635.6	4640.4	0.10
	Middle2	1	34.0	26.1	21.55	22.02	2.20	3535.7	3468.8	-1.89	2969.8	2894.2	-2.54
		2	34.0	26.1	21.64	22.01	1.71	3525.8	3482.4	-1.23	2944.1	2984.6	1.38
		3	34.0	26.0	21.10	21.37	1.29	3615.5	3591.1	-0.67	3035.8	3126.2	2.98
	Long1	1	214	80.0	21.40	21.58	0.82	22319.9	22165.4	-0.69	19205.4	19133.3	-0.38
		2	213.6	80.0	18.17	18.35	0.95	26406.0	26186.8	-0.83	23308.7	23159.9	-0.64
	Long2	1	207.3	66.0	22.37	22.53	0.70	20860.9	20731.1	-0.62	18395.2	18301.0	-0.51
		2	207.1	66.1	22.14	22.34	0.92	21052.0	20885.1	-0.79	18587.4	18424.2	-0.88
Average							**1.48**			**-0.92**			**0.92**

(1)EV driving ratio

There are two cases in which battery depleted before reaching the destination in geo-fencing area, but table5 shows EV time ratio is more than 95% in geo-fencing area. After learning, EV driving performance improved for all cases, as expected.

Table5: Result of the EV rate

Corse	no	EV_rate[%]_distance	EV_rate[%]_time
Middle1	1	95.00	97.03
Middle2	1	96.53	98.20

(2) CO_2 result

CO_2 benefit becomes worse as expected from -0.89g in table1 to 0.92g in table4 with Euro CO_2 calculation, because battery energy is remaining at the destination to achieve full EV driving in geo-fencing area.

Since Europe and Japan has different geography, CO_2 generating electricity in Europe is smaller than Japan. Therefore, remained energy in the battery at the destination has bigger impact in Europe because battery energy remained means more engine starting. Therefore, it is important that battery energy optimization takes the energy situation in each country into account.

5. Conclusion

The development of Toyota's Predictive EV Drive and validation of its benefit in real world usage is explained.

It can be confirmed that this control improves fuel efficiency by up to 0.98% and can reduced CO_2 emissions by up to 0.77% in Japan. This effect is similar than Euro data.

We will proceed with our developments to further refine fuel efficiency and expand the application and commercialization of geo-fencing function.