This is Harsh Meel, DE of the accumulator subsystem.
The team had been using 22Ah 96S1P EPS cells from EvoK and we had to procure a new set of cells for E13. This mail would briefly summarise the new method designed for Energy Estimation of the car using driver data collected by racing team.

Energy Estimation

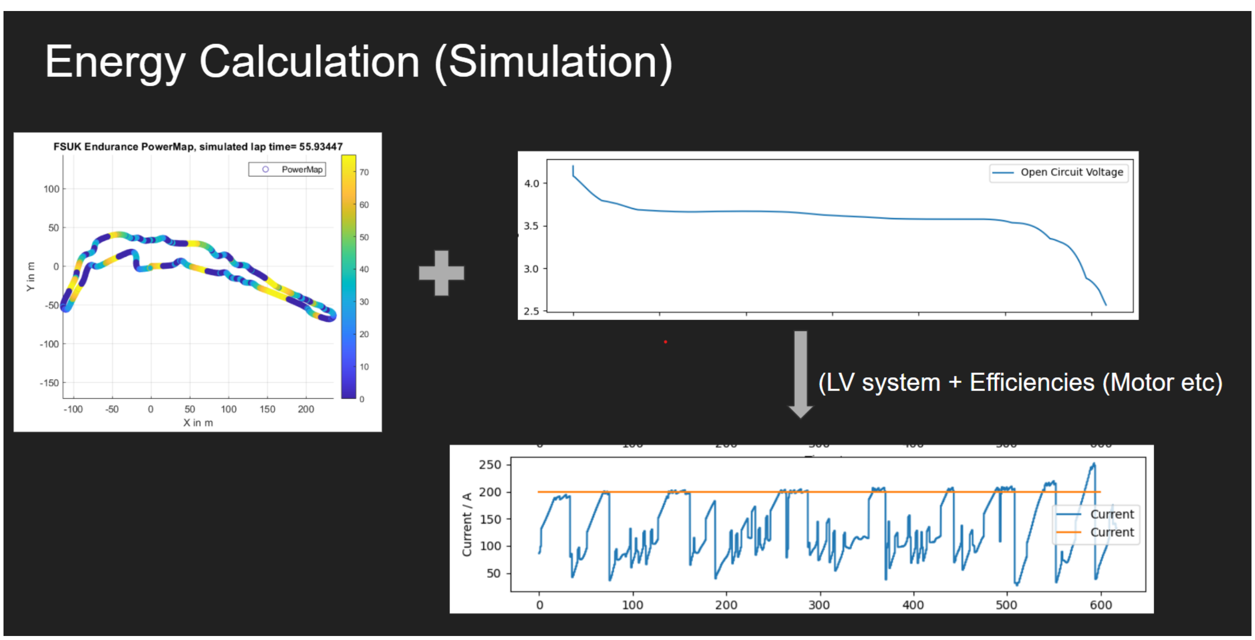
Here on I will use “E12” and “EvoK” names interchangeably for the previous year's car

Till **E12, we used to extrapolate the 9 lap data from EvoK run at FSUK 2019** to get the estimate of energy requirement. The safety factor would be, two laps of energy considered.

The errors from this interpolation can be :
1. There is an assumption that the driver would have driven the car as good or bad for the 22 laps as he did in the 9 laps in EvoK. Also, this meant that drivers are supposed to put similar performance as that of E12 drivers, and there is no quantified energy budget for them to push without worry.
2. Because the data is from the first half of endurance, the voltages were high and the currents were low. For the latter half, drop in the voltages will shoot the current up. Increasing the heat losses and losses in the powertrain due to high C rates.
3. There is no sound engineering logic behind the safety factor or any risk analysis.

So we tried a new method to find the energy requirement for the Endurance Run.The inputs were:
1. A lap simulation from a full car model gives us instantaneous mechanical power at every part of the FSUK lap.
2. Put this data in Cell Discharge Characteristics Transient model

From these two models, we get the Energy spent by the current car, running at its full engineering capacity on the optimum lap.



Lap Time Simulation

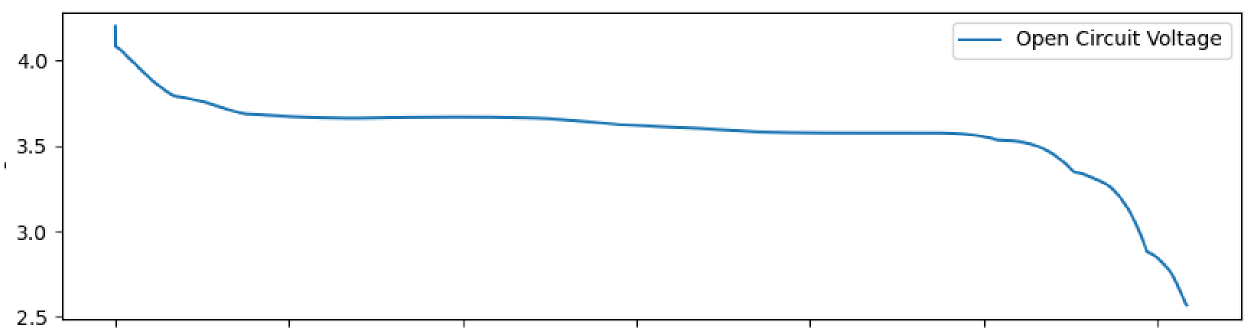
People from the Vehicle dynamics subsystem came up with the Lap time simulation.
Results:

1. The energy requirement per lap is **448.09 Wh/ lap** assuming the maximum available power of 72kW and Maximum Torque of 300 Nm. This is almost **2 times** what our driver consumed in FSUK 2019 in one of his best laps. The algorithm completed the lap in **52.16** seconds, which is far less than the average lap time of **80** seconds achieved by our driver.
2. Neglecting the drivetrain losses and assuming a maximum power of 80kW and maximum torque of 400 Nm, the net energy requirement turned out to be **495.45** Wh/lap with a lap time of 53.3 seconds.

The Transient Simulation

Working with the AMS subsystem, we came up with the transient Simulation. In this method we are calculating the energy consumption using the SoC algorithm.
First, the dataset containing power consumed by motors for one lap run is used, and the algorithm will run by repeating these values for the next 21 laps. First, run is directly calculated using the coulomb counting because of the direct availability of power consumption, but for further runs, the energy is calculated using the following algorithm:

Approximated SoC vs OCV curve of the cell used



The energy consumption is calculated using-

$\Delta E = \Delta SOC * Q_{Total} * V(t)$

ΔE is the energy consumption for each time step

Q_{Total} is the total capacity of the battery

$V(t)$ estimated voltage of cells at t seconds

Total energy consumption can be calculated by adding ΔE for all the time steps.

Total energy consumption after 22 laps will be = $E_{PT,\ simulation}$ = **10.731kWh**

- This energy (10.7 kWh) would be the engineering value to be provided for the car to give the maximum performance that is the least lap time.
- **This will be achievable if there is an Ideal Driver.**
- We know that this value is very high & our drivers won't perform so well.

Interpolation method

We need to have an estimate from previous data as well to see where our energy expenditure stands if we had the same driver performance as of EvoK Endurance run.

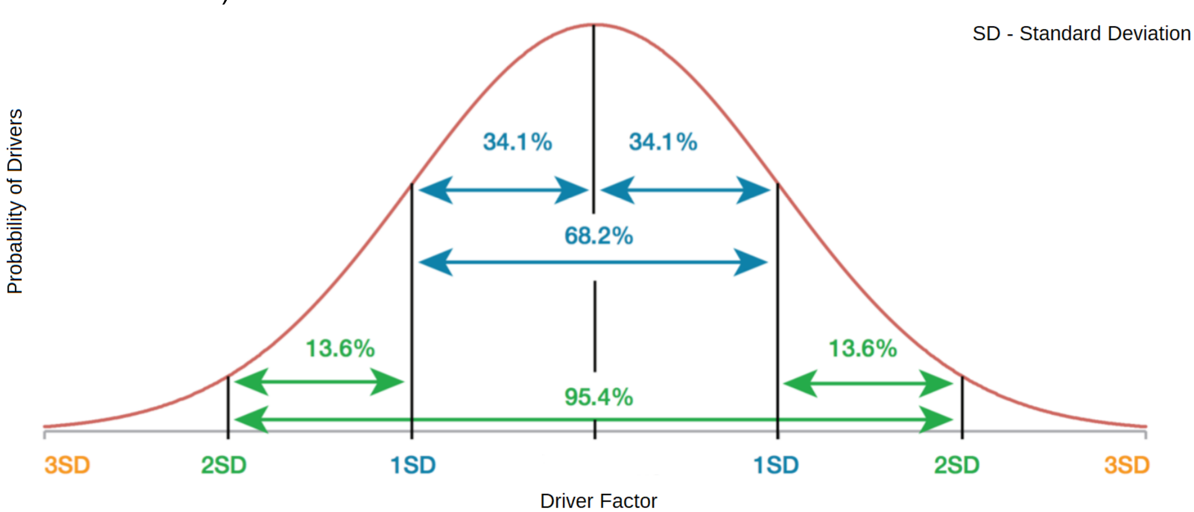
Total Energy- $E_{heat} + E_{PT,interpolation} + E_{LV}$ = Confidential Team Information. Not to be Published

Keeping a margin of 2 laps –
E_{22} = 5245.37 Wh
$E_{PT,interpolation}$ = 4936.74 Wh

These two energy values have such a high difference due to the Ideal driver condition. The driver of EvoK can't take out the same "juice" out of the car that the simulation can.

- We here get a range of values for E_{PT}.
- Maximum limit(ideal driver) - simulation value $E_{PT,\ simulation}$ = **10731 Wh**
- Lower limit ->Performance extracted by EvoK driver -> $E_{PT,interpolation}$ **= 4936.74 Wh**
- E13 driver is ought to perform in between these two ends.
- So we can use a "driver factor" that is based on the driver performance, which gives the newer driver enough space to push more and the battery energy more reliable.

Assuming the EvoK driver to be the base;
Driver factor of EvoK driver = f_0 = **1**
Driver factor of the simulation(Ideal) driver = f_L = 10731/4936.74 = **2.17**
To estimate the driver factor,
Assumption - Driver skills(Driver factor) varies as a normal distribution.
The Y-axis denotes the frequency or Number of Drivers and the X-axis has a driver factor (driver skill).
The mean value of this distribution will be the EvoK driver(*assuming him to be averagely skilled)* , and the max value (3 standard deviations) will be for the Simulation value.



We will be taking the value at 1st Standard deviation

$\boldsymbol{\sigma}$ = (2.17-1) / 3 = **0.39**

We will take the Upper limit of variation:

Driver factor = f_U = 1 + $\boldsymbol{\sigma}$ = 1.39

After relevant calculations:

Total Energy = 7230kWh

Scaling for 24 laps-

Total Energy = $E_{Total,factor}$ = Confidential Team Information. Not to be Published

Improved Driver Modelling - Aggression Prediction

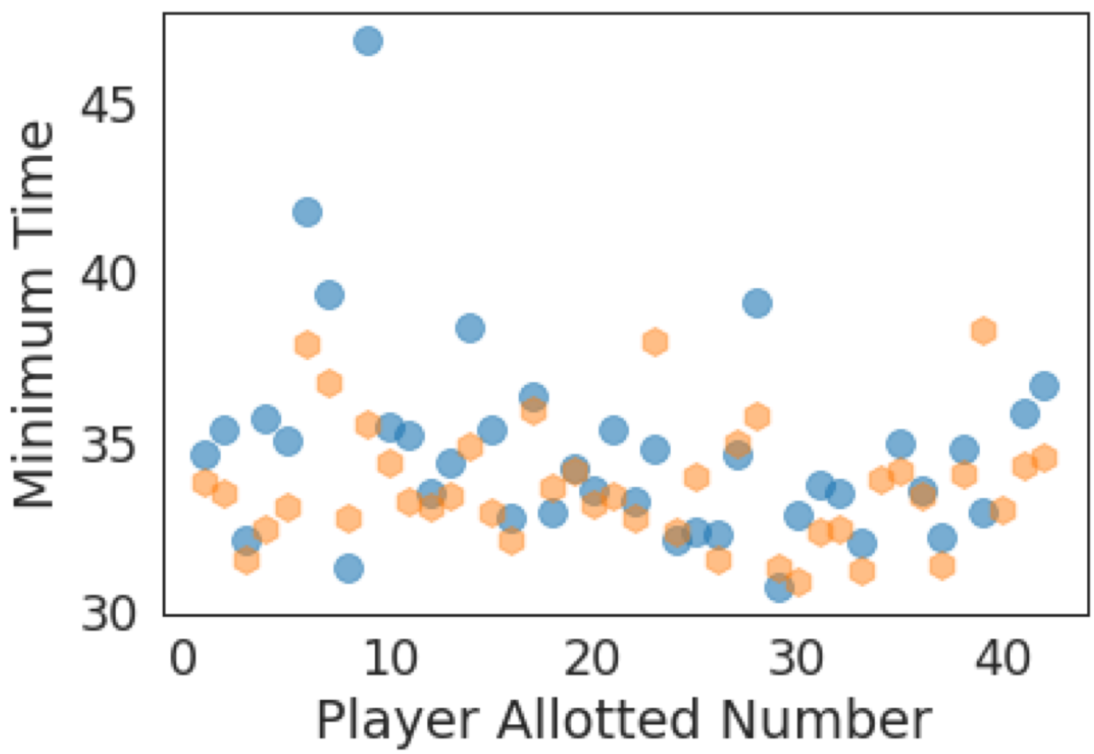
Data Collection

We needed actual driver data. The IITB Racing team went to Go Karting, Wadala with 22 drivers on two consecutive days. Some of the drivers went on both days. Each day every driver was supposed to participate in two sessions and in each session, they were supposed to complete 4 laps of the track; the best time taken by the driver has been noted for each session.

In all, there are supposed to be 84 data points, but some of the drivers had not participated in one of the sessions, so **we had a total of 82 data points**.

Data Processing

We have processed data for both sessions; we have attached the datasheet where our data have been pasted for both sessions, Day 1 up to the 41st cell i.e till “Ayush Jain”; after that, we have data till the 83rd cell for Day 2 data. We have removed the null values from the dataset. The time taken by the individual players has been decreased from session 1 to session 2 in most of the cases which can be seen from the below scatter plot.

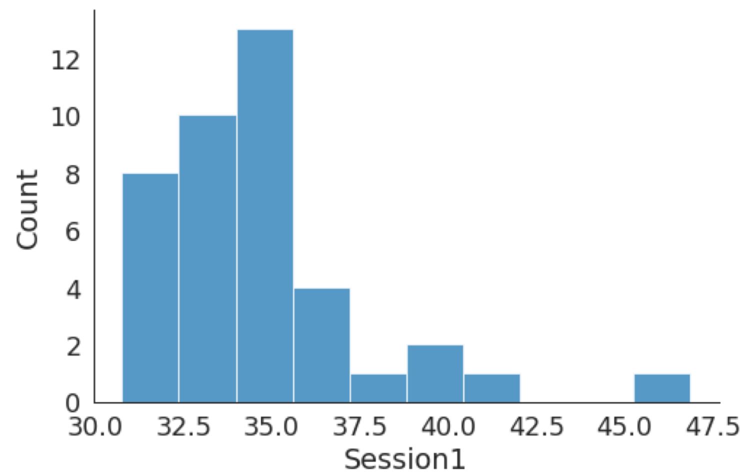


Index : Session 1 Session 2

This can be explained as drivers understood the handling of the go carts in the lap in session 1 and were able to execute better times next time around.

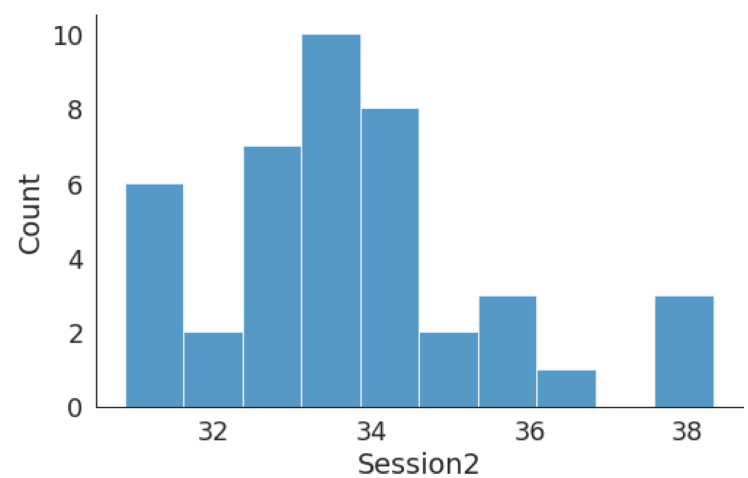
Session 1 Timing Analysis and Histogram

Mean	34.797550 s
Standard Deviation	3.009611 s
Minimum	30.741000 s
25% ile	32.898500 s
50% ile	34.509500 s
75% ile	35.389250 s
Maximum	46.879000 s



Session 2 Timing Analysis and Histogram

Mean	33.713952 s
Standard Deviation	1.802133 s
Minimum	30.875000 s
25% ile	32.509250 s
50% ile	33.410000 s
75% ile	34.349000 s
Maximum	38.317000 s

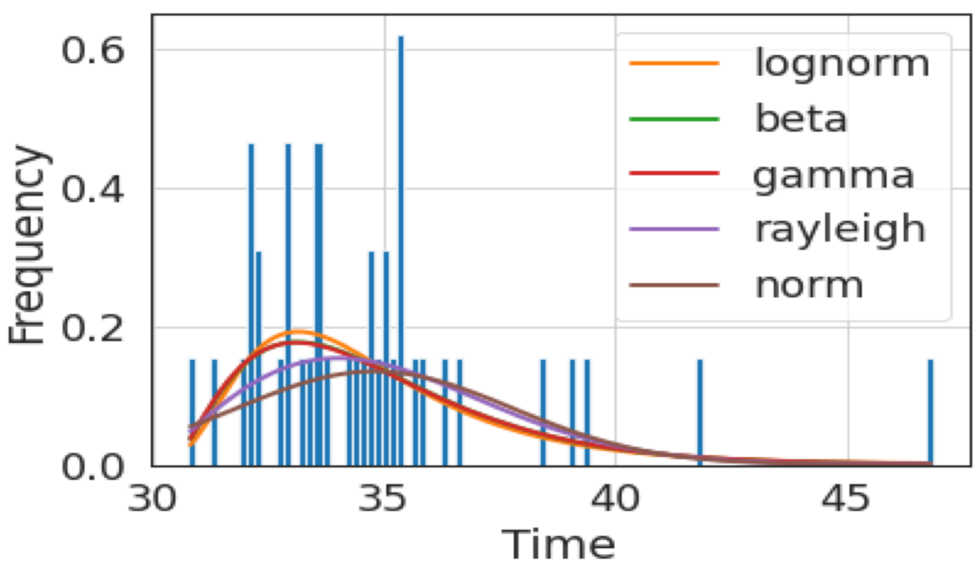


Different distribution were tried to fit to this data and Session 1 and 2 seems to follow **lognormal distribution**

Session 1 determination of best fit frequency distribution

	Sum square error	aic	bic	ks_statistic	ks_pvalue
Lognormal	0.990064	739.240113	-136.887957	0.098532	0.796319
Beta	0.998951	746.520286	-132.841626	0.114778	0.626361
Gamma	1.000558	740.841435	-136.466226	0.116171	0.611478
Rayleigh	1.030887	790.611445	-138.960632	0.175262	0.151774
Normal	1.093117	833.646146	-136.616080	0.193229	0.087843

Using **K – statistic** and **sum square error** as deciding factor, we assumed it to follow **Lognormal distribution**

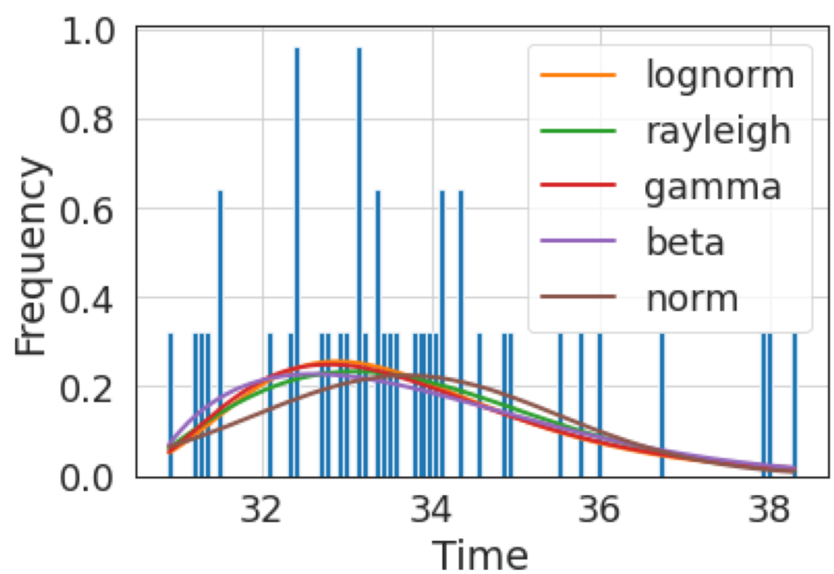


lognorm': {'s': 0.4902472888592949, 'loc': 29.380753019897234, 'scale': 4.789495868036521}

Session 2 determination of best fit frequency distribution

	Sum square error	aic	bic	ks_statistic	ks_pvalue
Lognormal	3.969857	471.693124	-87.862448	0.070595	0.975287
Rayleigh	3.986792	460.756857	-91.421340	0.094123	0.817177
Gamma	3.993453	467.205037	-87.613551	0.071584	0.971922
Beta	4.039781	456.355475	-83.391442	0.087509	0.876790
Normal	4.054842	473.273681	-90.710492	0.121108	0.529321

Using **K – statistic** and **sum square error** as deciding factor, we assumed it to follow **Lognormal distribution**

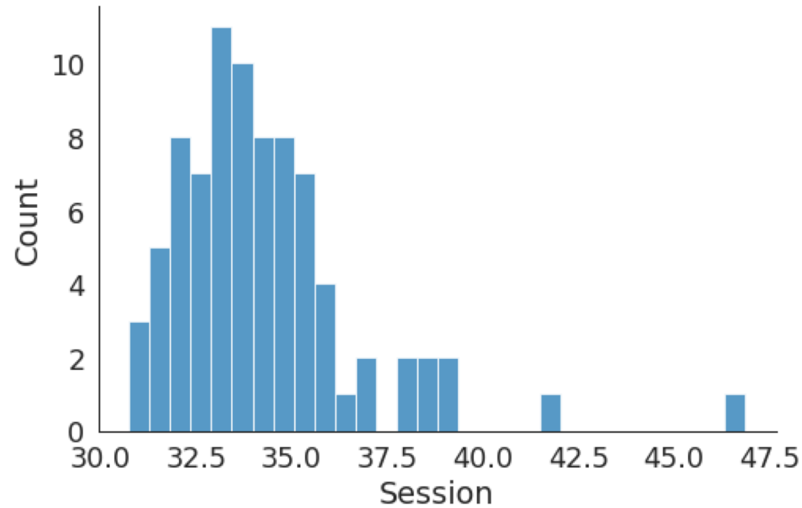


{'lognorm': {'s': 0.4902472888592949, 'loc': 29.380753019897234, 'scale': 4.789495868036521}}

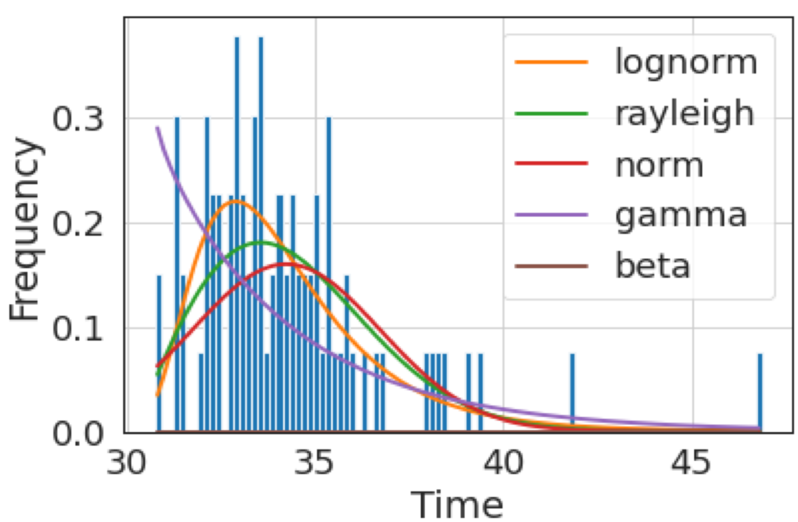
For the general distribution, we can assume that the people driving in the different sessions are independent drivers. Although we know that the time in session 2 has decreased for most of the drivers, in general we will have experienced drivers as well as poorly skilled drivers so, these data points can be fit in between. For the scope of study, relative difference in driving times is significant rather than improvement over sessions.

Analyzing all the data points:

Mean	34.242537 s
Standard Deviation (sample)	2.510384 s
Minimum	30.741000 s
25%	32.757500 s
50%	33.678000 s
75%	35.139500 s
Maximum	46.879000 s



	Sum square error	**aic**	**bic**	**ks_statistic**	**ks_pvalue**
Lognormal	0.375806	809.588735	-428.382822	0.054051	9.597613e-01
Rayleigh	0.402317	952.099584	-427.199810	0.105086	3.039085e-01
Normal	0.460685	1054.363466	-416.090968	0.124657	1.435673e-01
Gamma	0.650525	711.676046	-383.388780	0.205449	1.636826e-03
Beta	1.313411	inf	-321.368629	0.987805	2.335039e-157



'lognorm':

{'s': 0.46442351932862225,

'loc': 29.388376011163352,

*'scale': 4.34977398939630*5}

Results

From the overall analysis that we have done on all the 22 drivers, on Day 1 and Day 2 for both of the Session 1 and Session 2. We can conclude that the mean time of drivers was **34.233479 seconds** and to perform **better than 95%** of the population, the driver needs to cover the lap in **31.414683523060003 seconds.**

Aggression

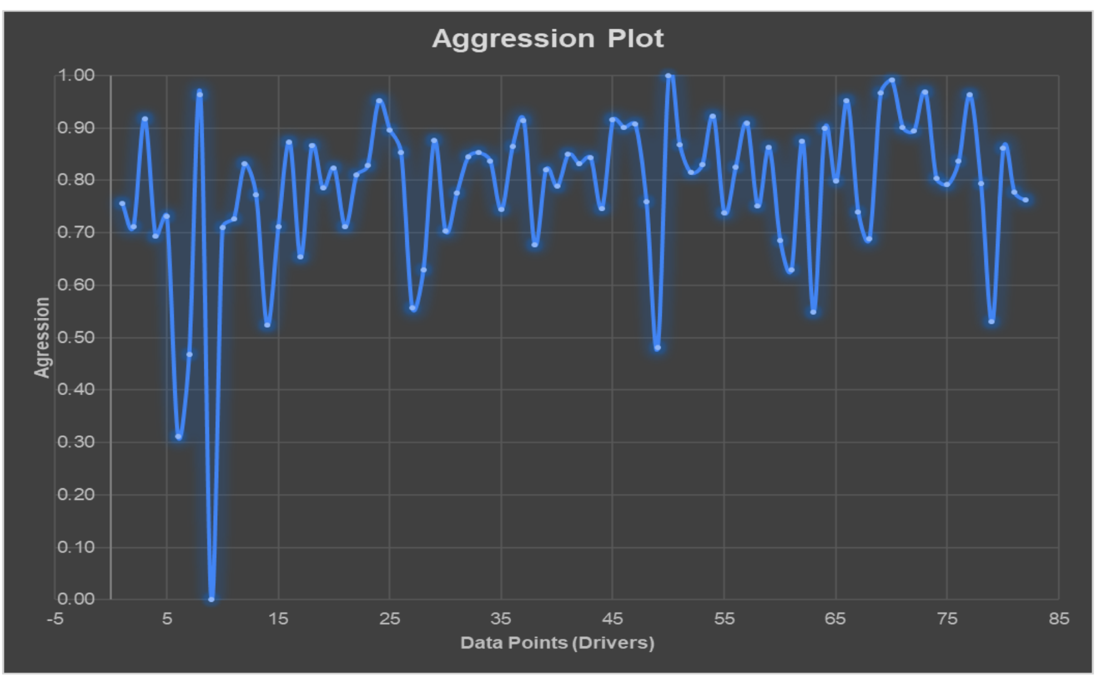
As explained in the problem statement, the aim of the study is to predict the driving aggressiveness of the population. We would define a new vale Aggression as:

$$\text{Aggression} = \frac{(T\_max - t)}{(T\_max - T\_min)}$$

where t = minimum lap time taken by a driver
T_max = maximum lap time taken by any driver
T_min = minimum lap time taken by any driver

From the data:
T_max = 46.879000 seconds
T_min = 30.741000 seconds

Aggression Calculation



Conclusion

Statistic	Time (log normal dist)	Aggression
Mean	34.233479 s	0.78
Variance	5.650830 s	0.02
Fastest 5%ile*	31.414684 s*	0.96
Fastest 25%ile*	32.568356 s*	0.89
Fastest 50%ile*	33.738150 s*	0.81
Fastest 75%ile*	35.338267 s*	0.72
Skewness	1.59	-2.13

*Note : * values are, for say fastest 25%ile, cutoff time taken by fastest(minimum lap time) 25%ile of all people. Similarly, for X%ile, its cutoff time is taken by the fastest X%ile of people.*

Therefore, the new driver factor for Battery energy calculation should be

= 1 + Aggression

Hence, we have found a way to map and control the driver factor based on the quality of drivers we are going to produce!

Large Population Predictor

One can use **theory of Confidence Interval** to predict the mean Aggression of population from the sample data.

Confidence interval:

Condition	Check
Randomized Sample	Sample consists of every type of driver who were asked to come to study on an open invitation. Thus, it is a random sample.
Sampling distribution is approximately Normal	Sample Distribution follows log-normal distribution. Hence it is approximately Normal. Also, n(=82) > 30 .
Independence	The sample data points are independent from each other.

Critical values of *t* for two-tailed tests

Significance level (α)

Degrees of freedom (*df*)	.2	.15	.1	.05	.025	.01	.005	.001
1	3.078	4.165	6.314	12.706	25.452	63.657	127.321	636.619
2	1.886	2.282	2.920	4.303	6.205	9.925	14.089	31.599
3	1.638	1.924	2.353	3.182	4.177	5.841	7.453	12.924
4	1.533	1.778	2.132	2.776	3.495	4.604	5.598	8.610
5	1.476	1.699	2.015	2.571	3.163	4.032	4.773	6.869
6	1.440	1.650	1.943	2.447	2.969	3.707	4.317	5.959
7	1.415	1.617	1.895	2.365	2.841	3.499	4.029	5.408
8	1.397	1.592	1.860	2.306	2.752	3.355	3.833	5.041
9	1.383	1.574	1.833	2.262	2.685	3.250	3.690	4.781
10	1.372	1.559	1.812	2.228	2.634	3.169	3.581	4.587
11	1.363	1.548	1.796	2.201	2.593	3.106	3.497	4.437
12	1.356	1.538	1.782	2.179	2.560	3.055	3.428	4.318
13	1.350	1.530	1.771	2.160	2.533	3.012	3.372	4.221
14	1.345	1.523	1.761	2.145	2.510	2.977	3.326	4.140
15	1.341	1.517	1.753	2.131	2.490	2.947	3.286	4.073
16	1.337	1.512	1.746	2.120	2.473	2.921	3.252	4.015
17	1.333	1.508	1.740	2.110	2.458	2.898	3.222	3.965
18	1.330	1.504	1.734	2.101	2.445	2.878	3.197	3.922
19	1.328	1.500	1.729	2.093	2.433	2.861	3.174	3.883
20	1.325	1.497	1.725	2.086	2.423	2.845	3.153	3.850
21	1.323	1.494	1.721	2.080	2.414	2.831	3.135	3.819
22	1.321	1.492	1.717	2.074	2.405	2.819	3.119	3.792
23	1.319	1.489	1.714	2.069	2.398	2.807	3.104	3.768
24	1.318	1.487	1.711	2.064	2.391	2.797	3.091	3.745
25	1.316	1.485	1.708	2.060	2.385	2.787	3.078	3.725
26	1.315	1.483	1.706	2.056	2.379	2.779	3.067	3.707
27	1.314	1.482	1.703	2.052	2.373	2.771	3.057	3.690
28	1.313	1.480	1.701	2.048	2.368	2.763	3.047	3.674
29	1.311	1.479	1.699	2.045	2.364	2.756	3.038	3.659
30	1.310	1.477	1.697	2.042	2.360	2.750	3.030	3.646
40	1.303	1.468	1.684	2.021	2.329	2.704	2.971	3.551
50	1.299	1.462	1.676	2.009	2.311	2.678	2.937	3.496
60	1.296	1.458	1.671	2.000	2.299	2.660	2.915	3.460
70	1.294	1.456	1.667	1.994	2.291	2.648	2.899	3.435
80	1.292	1.453	1.664	1.990	2.284	2.639	2.887	3.416
100	1.290	1.451	1.660	1.984	2.276	2.626	2.871	3.390
1000	1.282	1.441	1.646	1.962	2.245	2.581	2.813	3.300
Infinite	1.282	1.440	1.645	1.960	2.241	2.576	2.807	3.291

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Calculation:

Sample Mean ($\bar{x}$) = 34.242537 s

Degree of freedom (df) = n-1 = 81

Sample Standard Deviation (s) = 2.510384 s

Df~80

Significance level = 0.05

Critical value of t = 1.990

Mean time of population (95% confidence) = $\bar{x}$ t *

= 34.242537 s 1.990 * 2.510384 /

= **34.242537 +/- 0.551679 seconds**