International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 5,2025
https://theaspd.com/index.php

Revolutionizing EV Performance Prediction: Non-Linear Battery Models and Real-World Urban

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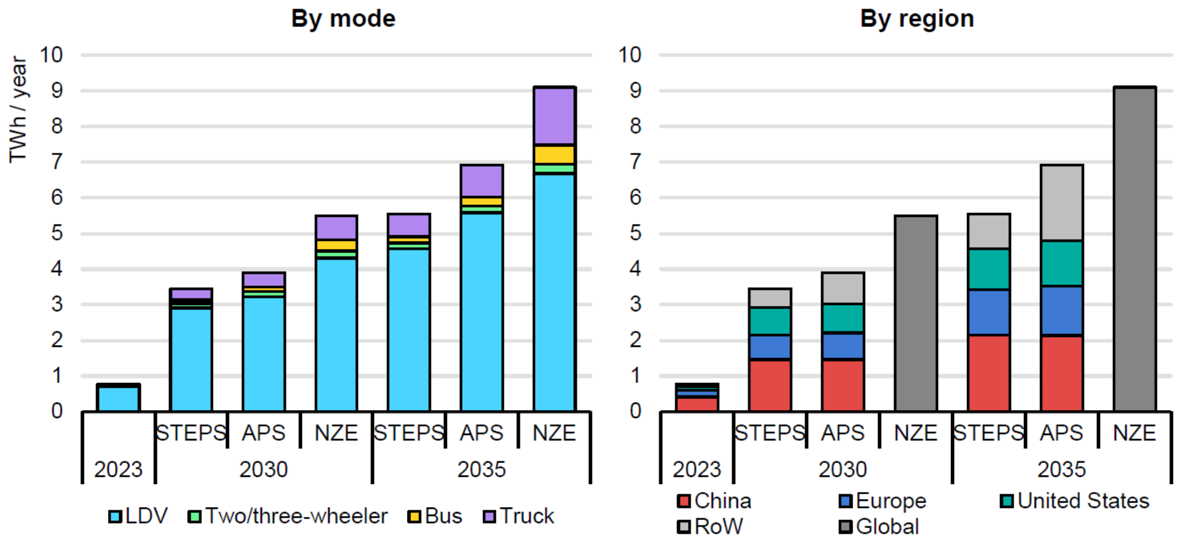
Abstract– *This paper unveils a transformative strategy for simulating electric vehicle (EV) functionality through the adoption of an elaborate battery framework that encapsulates non-linear discharge traits and exhaustive degradation processes. Diverging from earlier investigations that predominantly adopted linear discharge simplifications, this work formulates a computational platform to scrutinize EV range and battery endurance within a meticulously engineered urban driving cycle, rooted in empirical observations. Employing MATLAB/Simulink®, simulations are conducted on a prototypical EV-car, dissecting energy utilization, operational distance, and battery charge status under credible urban contexts. Outcomes from this endeavor showcase a pronounced elevation in forecasting precision over legacy approaches, delivering pivotal revelations that propel enhancements in EV structural design and battery operational protocols.*
Keywords– *Transportation; Electric vehicle; Drive-cycle; Mathematical modelling; Batteries*

INTRODUCTION

The growing importance of powertrain based EVs supports battery requirements adopting optimum performance to primary drivers for around 75% by 2035 [1]. This may include unhurried or rash driving scenarios considering wide ranges in driving advancements of EV-cars, EV-bikes or EV-trucks [2]. In most of the cases EV-cars have been first preference to study the overall effectiveness of the system on road owing to its elucidative understanding of Kinematic & longitudinal dynamic models [3, 4]. To study the overall enhancement of efficiency optimization, the evaluation of range and longevity is essential to enhance EV performance by calculating various mathematical scenarios using an on-board platform [5, 6]. However, due to oversimplification of EV-models & vehicular battery-models, predicting range and battery life calculation is challenging which is the granular source of energy [7]. Few review article suggest datasets of battery and real-time battery aging characteristics contributing dynamic logging of characteristic parameters for EV-models [8-10]. Also, few shortcomings to design a complex drive cycle (CYC_{mph}), accurate methodology and construction is of immense importance. Hence, few contributions elucidated in [11] -[16] helped understanding CYC_{mph} development. Most effective area where the scope of research emerged is - battery required for various real-time driving pattern constructions as per the implementation of CYC_{mph} in [17] - [26]. To determine characteristic features further with this roadblock a detailed qualitative & quantitative mathematical model, comprising various charge/discharging states, distinct modes pertaining to motion of EVs in the battery needs to be assessed. Researchers across the globe contributed various case studies on traditional customized CYC_{mph} in wide range of EV types. Various cities/countries from Hong Kong [27]-[29], India [30]-[33], Beijing [34, 35], Cairo [36] and Michigan [37] contributed on determining rigorous data-driven CYC_{mph} on various speed profiles and energy with respect to time. Studies on adaptability of CYC_{mph} in real world were reported also in [38, 39]. Novel advancements in comprehensive performance of EVs on various CYC_{mph} were witnessed and emerged as a benchmark to determine predict the overall battery performance in [40] - [48].



Notes: STEPS = Stated Policy Scenario; APS = Announced Pledges Scenario; NZE = Net Zero Emissions by 2050 Scenario; LDV = light-duty vehicle, including cars and vans; RoW = Rest of the world.

Fig. 1. Battery Demand between 2023-2035 [1].

This research work comprises a MATLAB/Simulink® based mathematical model which is developed to study ranges in 07 types of CYC_{mph} along with total force acting on the EV cars. Formulation and investigation of battery performance during acceleration & deceleration in motion cycles were addressed. Generating reference based calculations and determination of resistive-forces considering efficiency of sinusoidal EBMF motor is incorporated that further resulted comprehensive energy consumption. Multiple simulation runs on all the 07 types of CYC_{mph} were incorporated and analysed comparative logical assessment of EV-car motion cycle performance. Thus, this comprehensive work is sequentially elaborated following Section-(1) as introduction which includes literature survey and cited case studies pertaining to this topic. It is followed by Section-(2), method of proposed algorithm, elucidating the overall concept of the modelling with calculation. Section-(3) annotates simulation framework along with results and review of various responses is studied, further followed by Section-(4) results & discussion subsequently conclusions with future expected work in Section-(5).

METHOD OF PROPOSED ALGORITHM

Mathematical Modelling and Calculation of Characteristics for EV

Dynamic Force calculation, due to various values of acceleration, can be obtained considering each cycle segments of Velocity vs. time:

$$Acc = \frac{dVel}{dt}$$

Taking account of inertial coefficient for dynamic rotatory parts is considered by multiplying acceleration and total mass of the EV which implies calculation of dynamic force as:

$$F_{dyn} = \{1 + \gamma\} \times mass \times Acc$$

Here, γ = 0.1 inertial coefficient for dynamic rotatory parts. For specific resistance coefficient of the force, the rolling force to air resistance to it is calculated as:

$$F_{coeff} = F_{Air} + F_{Rotatory}$$

The force of air resistance is directly proportional to movement of the speed which convinces grated frontal area of EV as:

$$F_{Air} = Area_{Frontal} \times Streamline_{Coeff} \times Vel^2$$

Here, $AreaFrontal$ is frontal area of EV and $StreamlineCoeff$ is streamline coefficient which is further defined by:

$$StreamlineCoeff = \frac{1}{2} \times Res_{Aerodyn_{Air_{Coeff}}} \times \rho air$$

Here, ρ_{air} is 1.225kg/m^3 and $Res_{Aerodyn_{Air_{Coeff}}}$ is 0.35 N.sec^2/m.kg On substitution of all the parameters:

$$Streamline_{Coeff} = 0.21$$

The $Area_{Frontal}$ can be calculated as 0.9 for $Empirical_{Coeff}$ by height of EV and width of track (1585 mm) with height as 1705 mm:

$$AreaFrontal = height \times width \times 0.9 = 2.43m2 \ (7)$$

Therefore, the value of $F_{Rotatory}$ is calculated as:

$$F_{Rotatory} = Veh_m ass \times gravity \times f_{rotatory_f} \ (8)$$

Here, Vehicle mass is $Veh_m ass$; 9.81m/s^2 is the gravity; $f_{rotatory}$ is concrete + asphalt pavement the rotatory friction coefficient as 0.015. The calculation of force for traction with low and high terrain modes and braking modes is obtained by:

$$F_{Rotatory} = \begin{cases} F_{dyn} + F_{coeff} \\ F_{coeff} \\ F_{dyn} - F_{coeff} \end{cases}$$

Calculation of mechanical Power is:

$$Pow_{Mech} = F_k \times Vel$$

Furthermore, integration of power of traction over time is derived as:

$$Enrg_{Consumed} = \int_t^0 Pow_{thrust}(t)dt$$

Here, Pow_{thrust} is $\frac{Pow_{Mech_{thrust}}}{\eta_{reducer} \times \eta_{converter} \times \eta_{EV}}$. The electricity generated during regenerative braking mode is:

$$Enrg_{Generative} = \int_t^0 Pow_{breaking}(t)dt$$

Here, $Pow_{breaking}$is $\frac{Pow_{Mech_{thrust}}}{\eta_{reducer} \times \eta_{converter} \times \eta_{EV}}$. The resultant energy of the battery is determined as:

$$Enrg_{Final} = \begin{cases} E_{inertial} - Enrg_{Consumed}/\eta_{avg_{efficacy}} \\ E_{inertial} + Enrg_{Generative} \cdot \eta_{avg_{efficacy}} \end{cases}$$

Thus, the specific energy consumption for comparison across different cycle conditions is:

$$Enrg_{Specification} = \frac{Enrg}{3600 \times l}$$

Additionally, the SoC in % after driving 01 cycle of movement, considering full capacity, is:

$$SoC_{\%} = \frac{Enrg_{Final}}{E_{inertial}} \times 100$$

Thus, this simulation illustrates the linear consideration of SoC and mileage for the CYC_{mph} in detail

Algorithm 1. Simulation Illustration
Input: Drive cycle set {EUDC, HWFET, MIDC, NEDC, UDDS, US06, WLTC}, vehicle parameters, battery specifications.
Output: Performance metrics {total distance, net energy used, energy per kms, range, final SoC}
Initialize parameter set $P = \{m, C_{rr}, C_d, A, \rho, \eta_{motor}, \eta_{regen}, battery\ capacity, SoC_{initial}\}$
2: For each cycle ∈ {EUDC, HWFET, MIDC, NEDC, UDDS, US06, WLTC}
do Load velocity profile $v(t)$ from cycle data
4: Define t_{end}, Δt
Initialize state $S = \{t = 0,\ SoC = SoC_{initial}, net\ energy\ used = 0,\ total\ distance = 0\}$
6: while $t < t_{end}$
do Retrieve $v(t)$
8: Compute $a(t) = \frac{v(t) - v(t - \Delta t)}{\Delta t}$ Acceleration (m/s^2)

Compute forces $F = \{F_{inertia} = m \cdot a(t),\ F_{rolling} = C_{rr} \cdot m \cdot g,\ F_{aero} = 0.5 \cdot \rho \cdot C_d \cdot A \cdot v(t)^2\}$
$F_{total} = F_{inertia} + F_{rolling} + F_{aero}$ Total force (N)
Compute $P(t) = F_{total} \cdot \frac{v(t)}{1000}$ Power (kW)
if $P(t) > 0$
then
$\delta E = \frac{P(t)}{\eta_{motor}} \cdot \frac{\Delta t}{3600}$ Energy increment for propulsion (kWh)
else
$\delta E = P(t) \cdot \eta_{regen} \cdot \frac{\Delta t}{3600}$ Energy increment for regenerative braking (kWh)
end if
$net\ energy\ used = net\ energy\ used + \delta E$
$SoC = SoC - \frac{\delta E}{battery\ capacity}$
$total\ distance = total\ distance + v(t) \cdot \frac{\Delta t}{1000}$ Distance (kms)
$t = t + \Delta t$
end while
Compute metrics
$M = \left\{energy\ per\ km = \frac{(net\ energy\ used)}{total\ distance},\ range = \frac{battery\ capacity}{energy\ per\ km}, final\ SoC = SoC\right\}$
Output M
end

Features of the Choice of Drive Cycles for Mathematical Modelling of Battery Operating Parameters

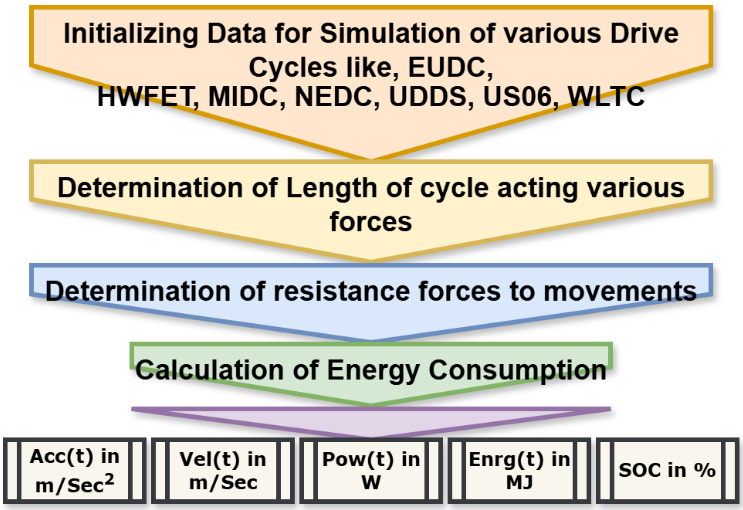


Fig. 2. Modelling Solution Flowchart.

Standardized drive cycles serve as critical tools for simulating real-world driving conditions to evaluate battery operating parameters in EVs as per the flow shown in Fig. 2 EUDC spans 4.99 kms in 6.67 min., reaching a maximum speed of 74.6 kms/h and averaging 44.92 kms/h, with one significant stop and accelerations up to 1.86 kms/h/s. This profile suits moderate-speed suburban scenarios, enabling energy efficiency assessments. MIDC covers 14.94 kms in 44.82 min., with a maximum speed of 38.87 kms/h and an average of 20 kms/h, featuring 10–20 stops and acceleration/deceleration rates up to 2.1 kms/h/s and 5.9 kms/h/s, respectively. Its stop-and-go pattern reflects urban congestion, ideal for modelling battery response in city traffic.
US06, an aggressive cycle, extends 12.88 kms over 10 min., achieving a maximum speed of 80.3 kms/h and averaging 77.3 kms/h, with six stops and rapid acceleration/deceleration rates up to 9.2 kms/h/s and 10.8 kms/h/s. This intensity tests battery limits under high-stress conditions. WLTC, a global

benchmark, covers 23.26 kms in 30 min., peaking at 131.3 kms/h and averaging 46.5 kms/h, with seven stops and rates up to 5.6 kms/h/s and 5.9 kms/h/s. Its mixed urban-highway profile supports comprehensive battery analysis. NEDC stretches 10.93 kms across 19.67 min., hitting 120 kms/h and averaging 33.3 kms/h, with ten stops and rates up to 3.75 kms/h/s, blending urban and suburban dynamics for balanced efficiency studies. UDDS, tailored for urban settings, covers 12 kms in 22.82 min., with a maximum speed of 56.7 kms/h and an average of 31.6 kms/h, including fifteen stops and rates up to 6.6 kms/h/s and 3.3 kms/h/s. Its frequent interruptions mirror city driving, crucial for discharge-cycle modelling. HWFET, simulating highway conditions, spans 10.6 kms in 12.75 min., peaking at 59.9 kms/h and averaging 49.9 kms/h, with no stops and rates up to 3.2 kms/h/s and 3.3 kms/h/s. This steady-state profile evaluates sustained battery performance. Each cycle's distinct features-distance, duration, speed, stops, and acceleration/deceleration rates-offer unique insights into battery behaviour. Selection for mathematical modelling hinges on the targeted driving scenario, ensuring EV battery designs align with operational demands across dynamic diverse conditions.

RESULTS AND DISCUSSION

MATLAB / Simulink® Implementation

Here, the simulation model depicts determination of 07 distinct CYC_{mph} with their responses, refer Fig. 3. To study the robustness and effectiveness of simulation, various improvements were incorporated towards understanding the behavior of battery performance at various driving conditions. So, adhering to the Japanese model electric car of Nissan Leaf, it has installed Lithium-Ion battery (192 cells in total having flat laminations) with maximum electrical motor power as 80 kW and a full range of 160 kms when the battery is charged full. Calculating furthermore considering battery as a power source, the total energy capacity and energy consumption in kJ/kms or kWh/kms is 86, 400 kJ and 540 kJ/kms or 0.15 kWh/kms. When considered equivalent fuel consumption in L/100 kms energy as per RON89, assuming energy content of RON89 is 9.7 kWh/L, equivalent L/100 kms is 1.55 L/100kms which directly compares to its counterpart. Moreover, the Sinusoidal EBMF motor is used with maximum P_{Output} of 80 kW, T_{Max} of 280 Nm that contributes to $Speed_{Max}$ of 145 kms/h and $Acceleration_{to_{100km/h}}$ is 11.5 sec. Therefore, the overall parameters are: Mass = 1500 kgs; $R_{rolling_{coefficienct}}$ = 0.015; $Drag_{Air_{coefficient}}$ = 0.21; $Area_{Frontal}$ = 2.2 m^2; $Air_{Density}$ = 1.2 kg/m^2; $Acceleration_G$ = 9.81 m/sec^2.

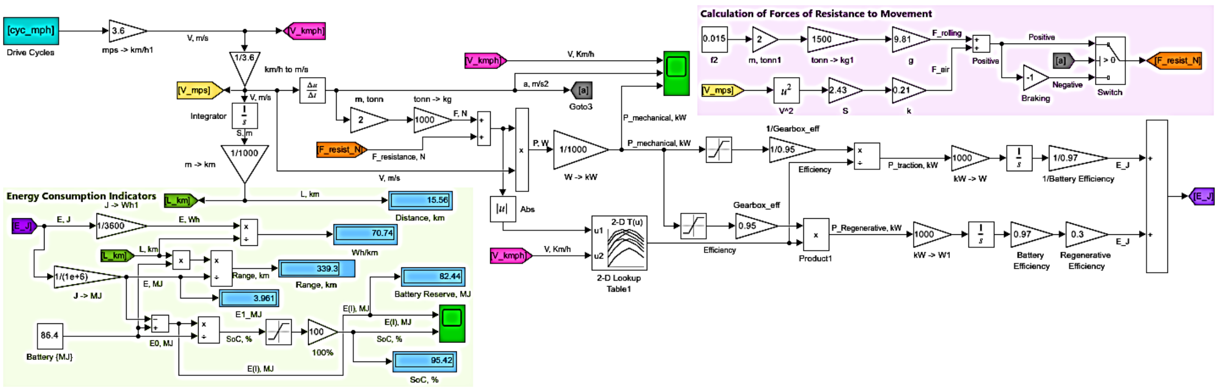
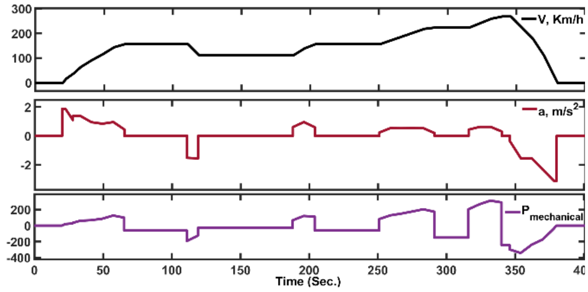
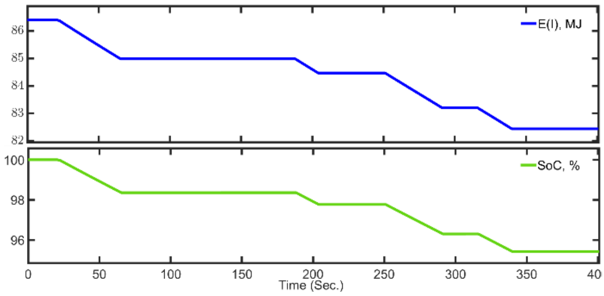


Fig. 3. Simulink Model Snapshot.

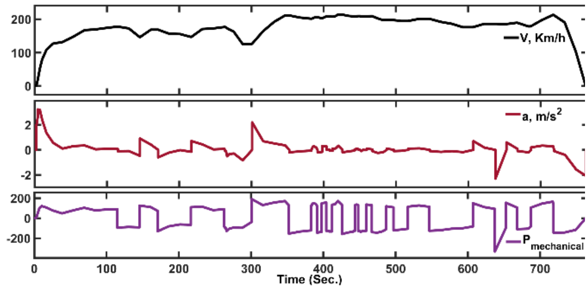
The representation of 2D lookup table elucidates efficiency of Nissan's motor which models as a function of two inputs, viz., $Motor_{Speed}$ and $Motor_{Torque}$. Irregular efficiency of motor is captured by giving 06 speed point ranges (from standstill to 10,000 rpm) and 07 torque point ranges (from 0 to 280 Nm). So, to adjust 06 speed and 07 torque points, i.e., 06 07 matrix, the efficiency data of PMSM and efficiency drop as per low & high speed/torque is assumed between 0.95—0.75 and 0.85—0.90 & 0.90—0.93, respectively. For verification & validation with power data the product of $(Torque, Speed, Efficiency)/9550$ results into Power. This ensures models' ruggedness in simulating all the CYC_{mph} conditions from lower-speeds to aggressive-speeds making it realistic to all the drives.


V, Km/h
a, m/s²
P mechanical
Time (Sec.)

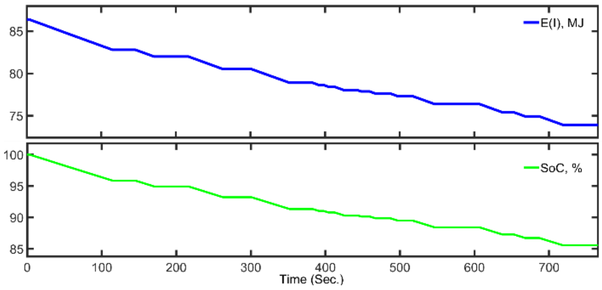
(a)


E(I), MJ
SoC, %
Time (Sec.)

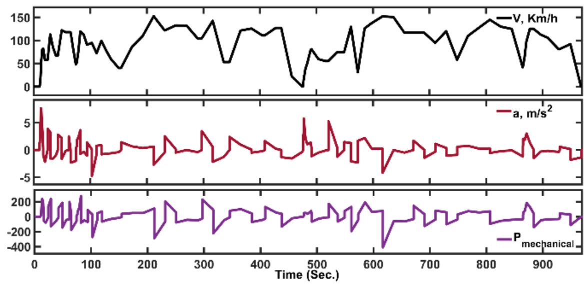
(b)


V, Km/h
a, m/s²
P mechanical
Time (Sec.)

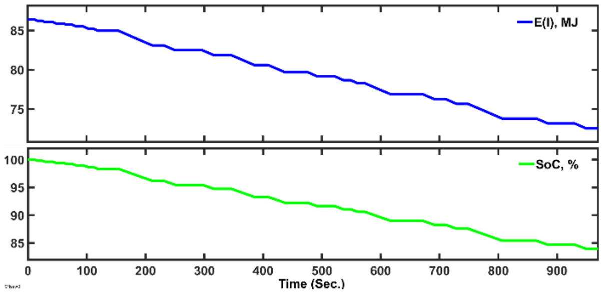
(c)


E(I), MJ
SoC, %
Time (Sec.)

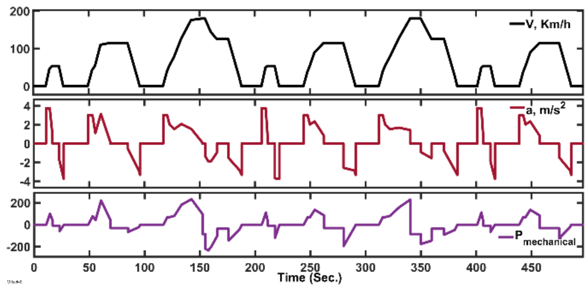
(d)


V, Km/h
a, m/s²
P mechanical
Time (Sec.)

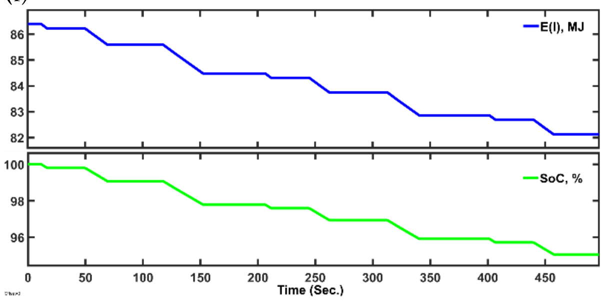
(e)


E(I), MJ
SoC, %
Time (Sec.)

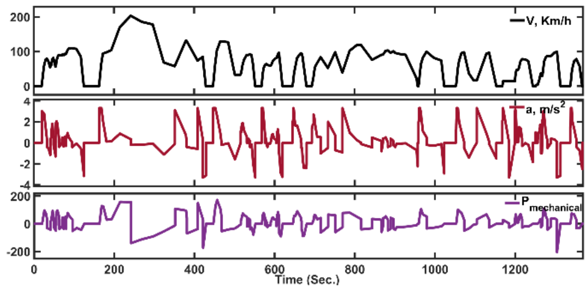
(f)


V, Km/h
a, m/s²
P mechanical
Time (Sec.)

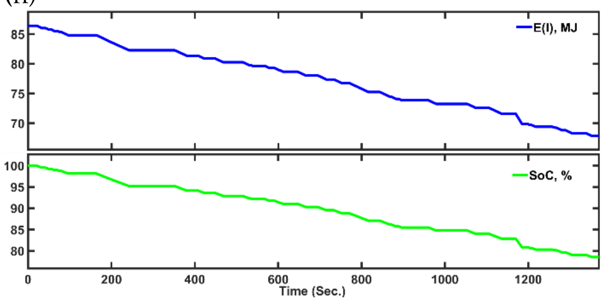
(g)


E(I), MJ
SoC, %
Time (Sec.)

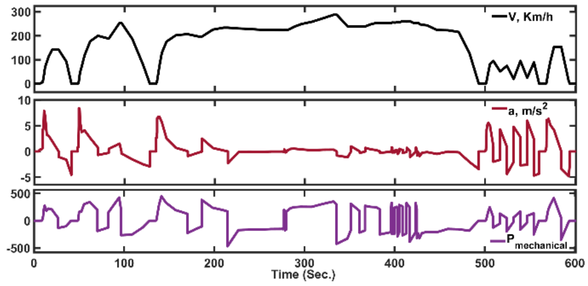
(h)


V, Km/h
a, m/s²
P mechanical
Time (Sec.)

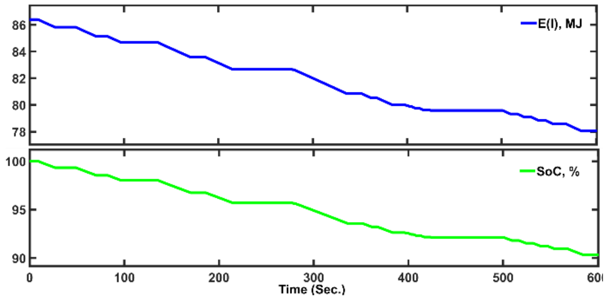
(i)


E(I), MJ
SoC, %
Time (Sec.)

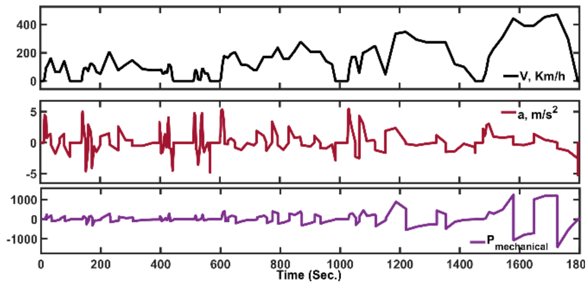
(j)



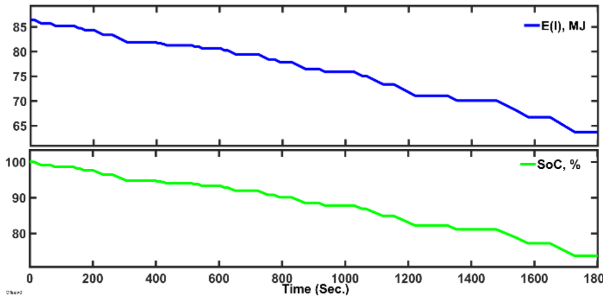
(k)



(l)



(m)



(n)

Fig. 4. Illustrated Independent Drive Cycle Characteristic Responses of (a) & (b) EUDC; (c) & (d) HWFET;
(e) & (f) MIDC; (g) & (h) NEDC; (i) & (j) UDDS; (k) & (l) US06; and (m) & (n) WLTC.

Table 1. Comparative Analysis of CYC_{mph} Obtained from Simulink*

Drive Cycle	Distance (in kms)	Specific Consumption (in Wh/kms)	Range (in kms)	Energy Consumption per Cycle (in MJ)	Battery Charge Reserve (in MJ)	Battery SoC (in %)
EUDC	15.560	070.740	339.300	003.961	082.440	095.420
MIDC	27.980	137.500	174.600	013.850	072.550	083.970
NEDC	08.591	138.200	173.600	004.275	082.130	095.050
WLTC	83.900	075.020	319.900	022.660	063.740	073.770
US06	28.860	080.340	298.700	008.347	078.050	090.340
HWFET	36.940	093.780	255.900	012.470	073.930	085.570
UDDS	26.810	192.20	124.900	018.550	067.850	078.530

**Note: Laptop Configuration: Processor 11th Gen Intel(R) Core(TM) i3 — —1115G4 @ 3.00GHz; Installed RAM 8.00 GB (7.79 GB usable); System type 64–bit operating system, x64-based processor*

Simulation outputs from the Simulink model quantify EV-car battery performance across seven standardized drive cycles, each defining unique operational conditions is illustrated comprehensively in Fig. 4[(a)-(n)]. The EUDC cycle, representing steady suburban driving, yields the lowest specific energy consumption (70.740 Wh/kms) and the longest range (339.300 kms), indicating optimal efficiency at consistent moderate speeds. In contrast, the UDDS cycle, emulating urban stop-and-go traffic, produces the highest specific energy consumption (192.200 Wh/kms) and the shortest range (124.900 kms), reflecting elevated energy demands from frequent acceleration and deceleration. The WLTC cycle, covering the greatest distance (83.900 kms) with a specific energy consumption of 75.020 Wh/kms, results in the lowest battery state of charge (73.770 %), demonstrating the effect of prolonged mixed driving on energy depletion.

Drive cycle characteristics significantly dictate battery performance. Urban profiles, such as UDDS and MIDC (137.500 Wh/kms), exhibit increased energy consumption due to repetitive acceleration and braking, whereas highway-centric cycles like HWFET (93.780 Wh/kms) and suburban cycles like EUDC demonstrates reduced energy use under sustained velocities. The Simulink model integrates physical parameters-rolling resistance, aerodynamic drag, and regenerative braking-to accurately simulate these variations. Energy consumption disparities, such as 18.550 MJ for UDDS versus 3.961 MJ for EUDC, corroborate the model's force and power computations, affirming its precision. These findings highlight the necessity of aligning drive cycle selection with EV-car operational contexts. Urban applications demand enhanced battery capacity and regenerative efficiency, while highway or suburban scenarios capitalize on lower energy consumption for extended range. The Simulink model's fidelity in replicating these trends establishes its value for optimizing battery management systems across diverse use cases.

CONCLUSION

This investigation delineates the pivotal influence of standardized drive cycles on EV battery performance assessment and enhancement. Simulations of seven cycles-EUDC, MIDC, NEDC, WLTC, US06, HWFET, and UDDS-via a Simulink model reveal the impact of driving conditions on energy consumption, range, and state of charge. Suburban cycles like EUDC exhibit minimal energy use (70.740 Wh/km) and maximum range (339.300 km), while urban cycles like UDDS show elevated consumption (192.200 Wh/km) and reduced range (124.900 km), reflecting the effect of traffic dynamics and speed fluctuations on efficiency. The Simulink model, embedding resistance forces and regenerative braking, delivers precise simulations of battery response across scenarios. This framework supports the development of battery designs and energy management tailored to specific operational demands-urban, suburban, or highway. The study validates the model's efficacy and underscores the importance of context-specific battery system optimization for contemporary EV applications. Future analyses could incorporate additional practical hardware implemented cycles, environmental variables (e.g., temperature, terrain), or refined battery dynamics. The present research provides a robust basis for advancing efficient, sustainable EV battery technologies.

Acknowledgement: We sincerely acknowledge BVDU CoE, Katraj, Pune, Maharashtra for vital technical support. We also acknowledge and appreciate support & contribution for generous financial backing from DYP IoTech, Pimpri, Pune along with PES's MCoE, Pune.

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