22th International Conference on Renewable Energies and Power Quality (ICREPQ'24)
Bilbao (Spain), 26th to 28th June 2024
Renewable Energy and Power Quality Journal (RE&PQJ)
ISSN 2172-038 X, Volume No.22, September 2024

Research on Interior Design of New Energy Vehicles under the Concept of Information Materialization

Jiaqi He [1], Hasnul Azwan Bin Azizan Mahdzir[2*] and Hong Chen[3]

[1] Faculty of Creative Arts
Universiti Teknologi MARA
Kedah, Malaysia

[2] Faculty of Creative Arts
Universiti Teknologi MARA
Kedah, Malaysia
E-mail:hasnul622@uitm.edu.my

[3] Faculty of Creative Arts
Universiti Teknologi MARA
Kedah, Malaysia

Abstract. This research focuses on the interior designing of electric vehicles (EVs), considered as new energy vehicles (NEVs), within the information materialization framework. The idea of information materialization refers to the quantifiable demonstrations of given data within the vehicle interior space, enhancing user interactions and experiences. Considering the State of Charge (SoC) as the crucial designing parameter, the research investigates the several implications of SoC on NEV interior designing. SoC, a critical parameter that reflects the battery's charging level, profoundly influence the merging of SoC data into the vehicle's dashboard or infotainment systems, ensuring seamless accessibility and intuitive interpretations for the driver. Instant alerts and notifications are designed based on SoC levels to provide real-time feedback and guidance to end users, optimizing driving ranges and strategies for charging. Furthermore, the study emphasizes the significance of customization options in SoC displaying formats and accommodates varying users preferences and requirements of visibility. Analysis of empirical and feedback from users, the research confirms the effectiveness of SoC-driven designing intervention in enhancing user experiences, safety, and overall functionalities interiors of NEV. The findings underscore the pivotal role of SoC as a fundamental designing parameter in shaping the next generations of NEV interiors and highlight the need for complete consideration of energy management aspects in future vehicle design endeavors.

Key words. Interior Designs, New Energy Vehicle (NEVs), Information Materializations, State of Charge (SoC), User Experience, Design Parameters.

1. Introduction

The Interior designing of vehicles has evolved by integrating several disciplines, such as the mindset of designing and ergonomic factors, into its system [1], [2]. This has resulted in a more sophisticated division of labor within the field, requiring a maximum level of professionalism. Additionally, the rise of advanced smart devices being used in vehicles has propelled the development of interior spaces towards a more intelligent and livable environment for humans. Consequently, consumers have developed new expectations and preferences for the interiors of the vehicles. Meeting the fundamental standards is no longer enough; interior design must now encompass innovative solutions in order to cater to the diverse and unique needs of users [3]. As the vehicle industry continues to evolve and design concepts evolve, the focus on user-oriented interior design has intensified [4]. Leveraging the power of digital design techniques, manufacturers strive to gain a competitive edge in the market through enhanced user experience. As a result, research has been taken on the design of Automobile products in order to stay current with user needs. Furthermore, the rise of intelligent networking has sparked a trend of multi-modal interior design for electric vehicles, incorporating elements such as networking and advanced technology.

The confluence of interior designs and new energy vehicles (NEVs) within the conceptual frameworks of Information Materializations presents an exciting horizon in automotive innovation and user experience improvements. As we shift towards sustainable transportation solutions, NEVs have risen to the fore frontier as a prime contender, embodying the principle of environmentalist consciousness and technological progress. At the core of this concept lies the interior environments of these vehicles, which go beyond their traditional roles as a mere transition space, and instead serve as a dynamic interface for human interactions, sharing of information, and sensory engagements. By harnessing the concept of Information Materialization, which involves translating data into tangibles and perceivable formats, NEVs are poised to revolutionize the way we perceive and engage with our vehicles. With the power of cutting-edge technologies like augmented realities, interactive displays, and adaptive lighting systems, designers have the ability to create captivating environments that seamlessly blend real-time data, tailored preferences, and environmental cues [5]. This perfect integration is further enhanced by the incorporation of nature-friendly materials, ergonomic designs, and flexible arrangement; ultimately showcasing the harmonious relationships between human driver and their personalized vehicular spaces. Our objective is to investigate the complexity of interior designs in NEVs, using the concept of Information Materializations to shed light on its abilities to revolutionize the dynamic between humans, vehicles, and the ever-evolving digital world they coexist in [6]. The vehicle industry is continuously evolving and with it, the design concepts are also transforming. As a result, vehicle interior design is becoming more focused on meeting the needs of users. By utilizing digital design techniques, the industry aims to stand out in the market by providing exceptional user experiences [7]. Keeping up with the changing trends, vehicle product development now relies heavily on conducting user research to better understand their needs and preferences. Furthermore, the incorporation of cutting-edge technologies in intelligent networking has brought about the rise of multi-modal electric vehicle interiors, including features like networking and AI.

2. Related Works

X. Yuan et al. [8] provide a critical examination of China's policy framework for new energy vehicles. It highlights the prioritization of electric vehicles in China's automotive industry development and the significant role of policy guidance and planning. Despite these efforts, challenges remain in technology development, market penetration, and infrastructure construction, indicating the need for continued efforts to achieve widespread adoption of new energy vehicles in China.

H. Gong et al. [9] investigated China's efforts in promoting new energy vehicles (NEVs) through initiatives like the Thousands of Vehicle, Ten City (TVTC) Program. It evaluates the progress of NEV deployment and highlights challenges such as lagging behind original plans and constraints in technology and pricing, particularly regarding lead-acid battery technology.

Z. Liu et al. [10] examine the current state and future prospects of main technology pathways for vehicles in China. It discusses the evolution of internal combustion engines towards simplicity through electric motor coupling, challenges facing battery electric vehicles, the significance of hybrid technologies, and the distinct applications of plugin hybrid electric vehicles, extended ranges electric vehicles, and fuel cell vehicles.

D. Siwiak and F. James [11] present intelligent evaluations of interior sound qualities (SQ) in electric vehicles (EVs) utilizing artificial neural networks and optimization algorithms. It includes subjective and objective SQ evaluations, incorporating acoustic characteristic parameters and optimizing the back-propagation neural network (BPNN) with simulated annealing (SA) and genetic algorithms (GA). The resulting SAGA-BPNN model accurately evaluates EV SQ and serves as a valuable tool for acoustic design in EVs.

E. Yang et al. [12] investigate the effectiveness of applying optical illusions to car interior design to enhance perceived roominess. The optical illusion was applied to instrument panels, door-trim armrests, and A-pillars, and alternative designs were evaluated using a questionnaire with 30 participants. Results indicate significantly improved perceived roominess with optical illusion-based designs, suggesting their potential for enhancing in-vehicle spaces.

M. Reed et al. [13] present a new concept in vehicle interior designs stemming from the ASPECTs programs and related study at UMTRI. It introduces physical manikins for seat measurements and techniques for integrated seat measurement into vehicle designs, leveraging revised versions of SAE seat positions and the ellipse model. These advancements allow for statistical posture and position prediction, tailored to specific user populations or individual occupant anthropometry.

J. Y. Kwon and D. Y. Ju [14] address the emerging era of fully autonomous vehicles and propose design methods for their interior spaces based on analyzing in-vehicle activity. Through consumer consciousness investigations, the study identifies needs to be related to resting, listening, and watching activities, aiming to satisfy customers' emotional experiences in the concepts of living spaces. This research fills a gap in the existing literature by offering new approaches to interior design through quantitative analysis of consumer needs.

A. Mazloumi and F. Mohammadreze [15] evaluate the interior design of the Shoka vehicle concerning accommodation for the Iranian population. Using descriptive-analytical methods and involving thirty Iranian male drivers, the study examines objective variables related to occupant packaging and subjective variables regarding driver mental workload and comfort. Findings suggest the need for optimization of seating angles and other ergonomic aspects to enhance driver comfort and customization of the vehicle's design.

J. F. Petiot et al. [16] examine user perception of vehicle interior craftsmanship across American and

French subjects. Using social science techniques and analytic methods like Multidimensional Scaling (MDS) and Principal Component Analysis (PCA), the paper investigates differences in perception relative to nationality. This research offers valuable insights into product perception and preferences, showcasing the application of scientific methods in understanding user perspectives.

Y. Li et al. [17] establish scenario-demanding-based interior design process frameworks for pure EVs. Using the KANO model, demands are sorted to inform the design framework, followed by the development of specific design programs. This research contributes to the theoretical advancement of pure electric vehicle interior design, offering valuable insights for future design practices.

3. Concept of Materialization

Materialization, as an abstraction pattern, has proven to be a valuable concept in various contexts. Essentially, it involves the relationships between a general group of categories, such as the model of a car, and a more specific object, such as a single car. The aim of this paper is to offer a quasi-formal semantic definition of materialization, using is-a and is-of abstraction, as well as class/met class correspondences. Furthermore, this concept brings with it new and powerful inheritance mechanisms. In addition, this paper will provide examples, properties, and extensions of materialization.[18] Incorporating materialization as an abstraction mechanism in conceptual modelings greatly enhances expressiveness by strategically introducing classification within the application's framework.

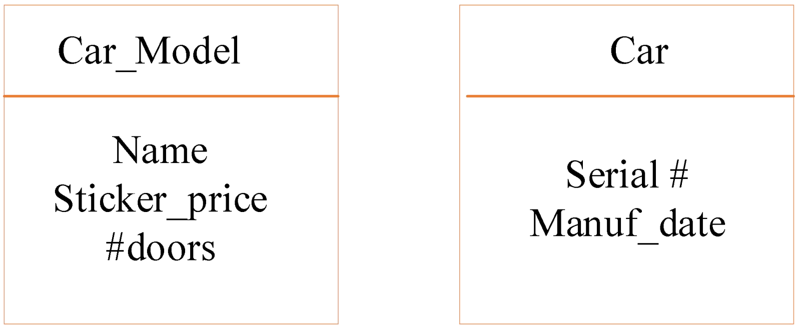

Fig. 1. Modelling of Materialization

Conceptual modeling is an important process that involves capturing and organizing elements of our physical and social environment in order to better comprehend and communicate them [19]. As this field advances, it aims to bridge the gaps between real-world concept and their representations in the conceptual model by introducing new, effective modeling tools. One such approach is object-oriented analysis, which focuses on understanding and representing application domains using user and domain expert perspectives, rather than design and implementation concerns. By utilizing semantically rich languages, analysts can more easily achieve their goals. One effective approach for expanding conceptual languages is by incorporating sophisticated domain-orient patterns [Coa92]. The added benefit of utilizing high-level patterns is their potential for reuse in similar application domains. In this study, we introduce and provide a formal definition for a particular extension. To illustrate, Figure 1 showcases an instance of materialization which we will delve into further in this paper. This example establishes a connection between the two categories. In the world of car dealerships, the information found in their catalogs is usually represented by a car model, while the details of individual cars owned by people are captured by the class Car [20]. Each instance of the car model pertains to a particular model, such as the FiatJetro, and outlines the shared characteristics among all the cars belonging to that model. According to [GS94], the relationship between the model and Car is one of materialization, with the former being more conceptual and the latter more specific [21].

Defining materialization involves precisely determining the qualities of this connection. Therefore, it carries both a sense of generalization (identifying a category of cars and its subgroups for particular models) and classification (a distinct car model, such as Fiat Retro, can be represented as an example of a group of car models). However, neither of these abstraction techniques fully captures the intended meaning. Each individual concrete car, such as one produced by Bico, corresponds uniquely to a single model, such as the Fiat Retro. Conversely, there can be multiple cars sharing the same model. This relationship is expressed through a materialization with a cardinality of (1, 1) from the concrete class to the model class while allowing a cardinality of (0, n) from the model class to the concrete class. Concrete cars are imbued with certain attributes inherited from their corresponding model. Hence, it is imperative to delineate the inheritance properties of materialization.

A. Information Materialization

Materialization in conceptual schema construction introduces a fresh dimension for analysts, offering enhanced flexibility when modeling segments of reality. For a class C to materialize a class A, C must occupy a more concrete position than A in the abstractness hierarchy, and the relationship between A and C must adhere to cardinalities of (1, l) from C to A and (0, n) from A to C. It's noteworthy that the (0, n) cardinality can be adjusted to align more closely with the real-world semantics being represented. Once materialization is integrated into the schema, numerous instances arise. The ensuing list provides merely a brief sampling:

Consider the conceptualization of air travel. This entails the notion of an itinerary, representing a journey from an origin to a destination, encompassing attributes such as distance. This itinerary could be materialized as a class of flights, pertaining to a particular airline, with associated details like price, available days of the week, and seasonal variations. Moreover, this class of flights could be further materialized into specific instances for individual calendar days, incorporating elements such as date, assigned aircraft, and crew. This example exemplifies the common occurrence of a lack of distinct terminology in natural languages to precisely denote various levels of materialized concepts. Frequently, the same term is utilized across different levels, with ambiguity mitigated by contextual cues within the linguistic or pragmatic context of communication.

4. Proposed Methodology

The research process integrates the concept of information materialization, transforming abstract data into tangible forms within the car's environment. Figure 1 depicts a systematic approach beginning with data acquisition from various sources, including car sensors and driver surveys.

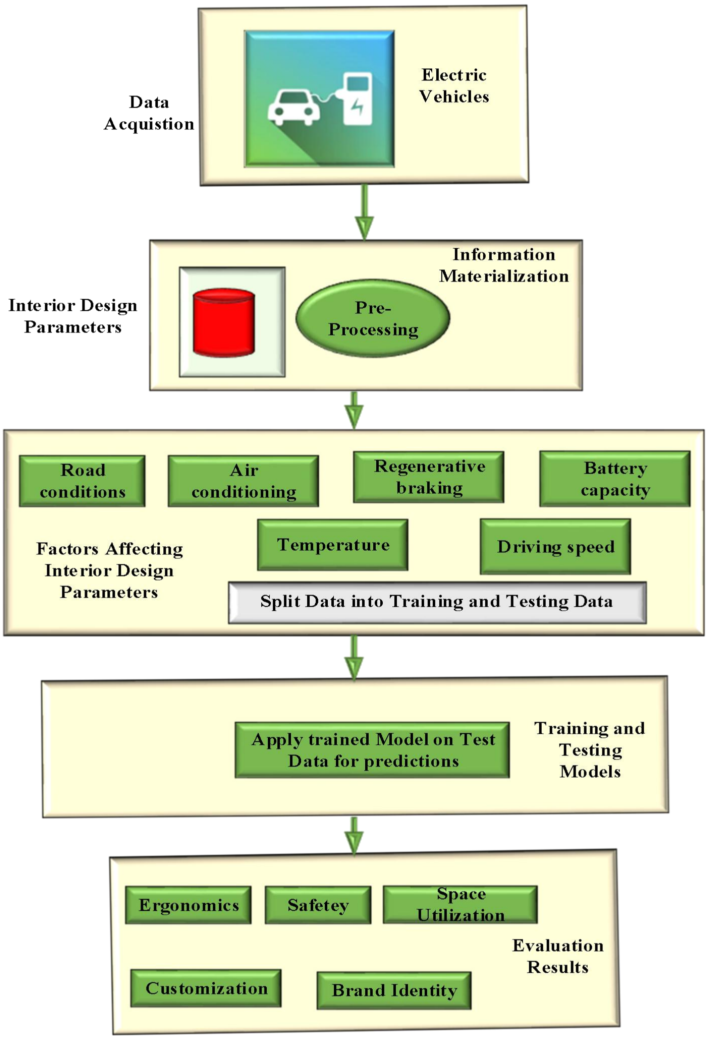

Fig. 2. Proposed Methodology of Interior Design of New Energy Vehicle Using Information

This data undergoes pre-processing, ensuring it's cleaned and formatted for analysis. Subsequently, the data is divided into phase of training and phase of test sets for machine learning model development. Predictions generated by the trained model inform the design process, offering insights into factors such as ergonomics, safety, and space utilization. These considerations are vital for creating interiors that are not only comfortable and functional but also informative and engaging for drivers and passengers. Through this comprehensive approach, the integration of information materialization promises to enhance the overall experience of new energy vehicles, aligning design elements with user preferences and performance metrics.

A. Modelling of Proposed Methodology – Electric Vehicles and Battery Modelling

The objective of the models is to assess battery aging across various driving conditions, using a compact car as the reference model. The models, shown in Figure 1, comprise three primary components: the longitudinal dynamic of the vehicles, the powertrain models, and the battery packs with their associated thermals dynamic.

1) Electric Vehicle Modelling

There are primarily two approaches to powertrain modelling [26]. The first is the backwards-facing approach, where powertrains state are calculated based on the input of the vehicle velocity profiles. Conversely, the forward-facing approaches adhere to the natural powertrain causalities by utilizing the throttle positions as inputs. The model in this study adopts a mixed forward-backward facing approach, as illustrated in Figure 1. This hybrid modelling approach facilitates the inclusion of drive performance loss introduced by the battery aging algorithms. Commencing with the forward-face part, the driver's accomplishment on the accelerator to achieve an expected speed is modeled using simple proportional regulators. Consequently, traction torque requests B_n^{rep} are determined based on the variance between the references (driver desire longitudinal speed/velocity) and the actual speeds of the vehicle.

$$B_n^{rep} = f_m \varepsilon = f_m(\beta_{ref} - \beta) \tag{1}$$

Where f_m is the proportional gains. Computed motor current is as follows:

$$i_m^{req} = \frac{T_m^{req}}{D_m} \tag{2}$$

The provided passage discusses a control strategy for an electric motor, specifically focusing on the torque constant D_m and the saturation of motor current $I_{\max}$. The requested motor current undergoes a saturation process, limiting it to $I_{\max}$. This $I_{\max}$ value is determined based on the outputs of the aging management strategy. In simpler terms, the motor current is adjusted according to the torque constant, and the resulting value is capped at Imax,1, which is calculated using information from the aging management strategy.

$$I_{\max} = f(I_{\max}^{cell}, \kappa_m, \overline{\Gamma_m}) = \frac{I_{\max}^{cell} S_p}{\omega_m k_m} \overline{\eta_m} \tag{3}$$

The given passage outlines factors contributing to electric motor efficiency, involving variables such as efficacy of electric motor ($\overline{\Gamma_m}$), battery packs voltages (S_p) and motor rotational speed (κ_m). The control variablesImax cells serves to limit battery cell currents, affecting vehicle acceleration and batteries recharging period. In Figure 1, the connection between $I_{\max}^{cell}$ and $I_{\max}$ is depicted by the function $f(.)$. The vehicle speeds is then determined from the motor's provided current (i_m^{sat} through the calculation of vehicle longitudinal dynamics.

$$M_c = i_m^{sat} \frac{k_m r_t}{K_w} - \frac{1}{2}\rho_a v^2 C_x A - F_r \tag{4}$$

The passage describes the modelling of power provided by the tractions motors for vehicle motions, incorporating various parameters such as vehicle mass (M), speed (v), gear ratio (r_t), wheel radius (K_w), rolling resistance (F_r), drag coefficient (C_x), air density (ρ_a), and vehicle cross-section areas (A). The power generated by the traction motors is influenced by these factors, and the model is expressed as follows:

$$P_m = \frac{k_m i_m^{sat} v}{R_\omega rt} = k_m i_m^{sat} \omega_m = R_m^{sat} \omega_m \tag{5}$$

with R_m^{sat} motor torques. In the back facing portions, the electrics machines is modelled as an efficacy maps which compute the batteries powers:

$$P_b = \begin{Bmatrix} \dfrac{P_m}{\psi_m(P_m)}, & if\ P_m \geq 0\,(Motor) \\ P_m \eta_m(P_m) & if\ P_m < 0\,(generator) \end{Bmatrix} \tag{6}$$

Here, ψ_m indicates motor efficiencies. The cell powers requests are $P_{cell} = \frac{P_b}{Cell}$ with $n_{cell} = n_s x n_p$ the cumulative number of cell of the batteries packs and $n_s\ and\ n_p$ correspondingly the numbers of cell in series and parallels configurations. Here, an A13 cylindrical LiFePO4 cells with nominals voltages of 3.4 (V) and characterized by a nominals capacities $Q_{nom} = 2.8(Ah)$ is considered. A series/parallels configurations with ns = 120 and np = 28 is selected, resulting a cumulative of 2860 cells.

2) Battery Cell Modelling

As highlighted in the introduction, the intricacies of modelling aging phenomena pose a formidable challenge, leading many researchers to adopt semi-empirical models in their contributions. In our framework, we embrace a similar approach to formulate a control-oriented model. To facilitate the modelling process, we make use of certain simplifying assumptions.

1) Our model operates under the assumption that a Battery Management System (BMS) is in place to ensure the balancing of all cell within the batteries pack.
2) We present an averaged model that intentionally overlooks cell polarization for simplification.
3) While the model incorporates temperature considerations, we posit the presence of an energy management system within the BMS.

Given these assumption, the battery packs is conceptualized as a singular, extensive cell, characterized by equivalent circuits comprising a source of voltage (v_{oc}) and a resistances (R_{cell}) that represents Joule loss. The open circuits voltages of the battery is contingent upon the State of Charge (SoC), while its resistance typically varies based on factors such as aging and temperature. Consequently, the current flowing through the cell is expressed as follows:

$$i_{cell} = \frac{v_{oc} - \sqrt{v_{oc}^2 - 4R_{cell}P_{cell}}}{2R_{cell}} \tag{7}$$

The cell SoC dynamic takes the following expressions:

$$S\dot{o}C = -\frac{i_{cell}}{Q} \tag{8}$$

With Q denoting the cell capacities, which diminishes over time due to aging, the battery aging model, as previously demonstrated in, is derive from and expanded from the Hybrid Electric Vehicle (HEV) scenarios to the Electric Vehicle (EV) context. Consequently, the rate of capacity decline concerning the processed Ampere-hours (A_h) is articulated as follow:

$$\begin{cases} \dfrac{dQ}{dAh} = -\dfrac{m}{100}\alpha \quad SoC \exp\left(\dfrac{-E_a + \phi \mid I_{cell}}{R_g(273.15+T)}\right)Ah^{z-1} \\ \dot{A}h \end{cases} \tag{9}$$

With the next equations modelling the Ah throughputs as the cumulative currents process by the cells. The parameter E_a is the activations energies, equal to 33.6 (kJ/mol), and the universals gas constants. ϕ and m are identify from experiment datas. α_{SoC} is a penalize factors that accelerates the age for minimum and maximum SoC.

$$\alpha_{SoC} = l(1 + se^{l(SoC_{\min} - SoC)})(1 + se^{b(SoC - SoC_{\max})}) \tag{10}$$

with $SoC_{\min}$, $SoC_{\max}$, l , s , and b empirically determined shaping parameters (Figure 3). The major stress factor affects the cell agings behaviors are: its SoC, its temperatures, and the C-rates I_{cell} , i.e., the operates currents normalize with regard to the nominals cells capacities Q_{nom}. Battery age lead also to an increment of the internals resistances. Hence, the subsequent linear relationships among a resistances increments ΔR_{cell} and maximum capacities decrements ΔQ is introduced:

$$\Delta R_{cell} = -q_{res}\Delta Q \tag{11}$$

with q_{res} deriving from the experiment datas. Eventually, recalls that the temperatures dependencies of the cells internals resistances is expressed by,

$$R_{cell}^1 = R_{cell,0^e}\left(\frac{D_1}{D - D_2}\right) \tag{12}$$

with R_{cell}^1 the nominal cell resistance and D_1 , D_2 identified parameters, the following is obtained:

$$R_{cell} = R_{cell}^1 + \Delta R_{cell} \tag{13}$$

It's important to recognize that the proposed models relies on empirical data and may exhibit variations depending on the actuals characteristics of the cells in uses. While the frameworks requires an aging models, it does not make use of any specific aspects inherent to the proposed models.

3) Thermal Management

Temperatures is one of the major factors increase battery agings. For this reasons, a common practices in automotives company is to introducing a batteries coolings systems in order to controls the temperatures to a achieved values T . Here, we considering an air-cooling battery packs.

$$\dot{Q}_{ev} = \dot{m}f1C_p, f_1(T_i - T_{0,1}) \tag{14}$$

where C_p, f_1 is the specific temperature capacities of airs, T_i and $T_{0,1}$ the air temperatures at the evaporator's inputs and outputs respectively. Thus, the cooled system is entered into the batteries packs, leads to the following energies balances:

$$-\dot{Q}_b = \dot{m}f_1C_p, f_1(T_{0,1} - T_{0,2}) \tag{15}$$

Where, $\dot{Q}_b$ is the heat exchanges the batteries and airs, and $T_{0,2}$ the air temperatures after the battery's packs. Under the assumptions of a same temperature's distributions $\dot{Q}_b$ and modelling the heat produced by the battery packs as $R_b i_b^2$, $\dot{Q}_b$ is rewritten as follow:

$$\dot{Q}_b = R_b i_b^2 + \frac{T_{room} - T}{R_{conv}} \tag{16}$$

with T_{room} the uniform temperatures, R_b the cumulative battery packs resistances, i_b^2 the battery packs currents, and R_{conv} the heat resistances inbetween the batteries and the surrounding. Assume no other thermal exchanges takes places and $T_i = T_{0,2}$, the following eequation holds true:

$$\dot{Q}_b = \dot{Q}_{ev} \tag{17}$$

It's important to recognize that the propose models relies on empirical data and may exhibit variations depends on the normal characteristics of the cells in uses. While the frameworks requires an age models, it do not make use of any particular aspects inherent to the proposing models.

$$P_{cool} = \frac{1}{\eta_{cell} COP} \dot{Q}ev \tag{18}$$

Here, COP represents the coefficients of performances of the cooling systems. In the end, the total powers required for each cells is raised by P_{cool}, resulting in the following equation:

$$P_{cell}^{tot} = P_{cell} + P_{cool} \tag{19}$$

Ultimately, the overall power demand for individual cells experiences an increment due to the addition of P_{cool} which can be expressed through the following equation:

4) Drivers Behavior Learnings

The battery aging models underscores the significance of cell currents as a key stress factor. The cell current is largely influenced by the instantaneous torque requested by the driver. The driving styles play a crucial role in shaping the aging dynamics. Here, a model is proposed to characterize the driver behaviors, along with learning mechanisms enabling the models to adjust to variations in the driving styles. Following a similar approach to the actions of the driver are depicted through a Markov chain stochastics processes, with state represented by $w(j) = w_m$, where 'n' signifies the number of states.

$$T_{mn} = P(w(j+1) = w_n \mid w(j) = w_m) = \lambda_{mn} \tag{20}$$

The transitions matrix can be acquired through offline learning or updated dynamically as new transition are records online. This allows for the continual learning of the driver models, specifically the driver needed speeds, by adapting Equation (20) in real-time. Assuming, at a given time instants $(j+1)$, the last and current state are denoted as w_m and w_n respectively, the adaptation process takes place as follows:

$$\Delta\lambda_{mn}(j+1) = \overline{\lambda} \sum_{n=1}^{S} \delta_{mn}(j+1), \;\; forall\, m \in \{1, \ldots\ldots, s\} \tag{21}$$

Here, $\Delta\lambda_{mn}$ belongs to the set {0, 1} and represents the magnitude of the probability update. The function δ_{mn} equals 1 only when the transitions from states $m \in \{1, \ldots\ldots, s\}$ is active; otherwise, δ_{mn} is set to 0. To ensure that the transition probabilities originating from each node δ_{mn} add up to one, the following updates rules is introducding:

$$T_{mn}(j+1) = (1 - \Delta\lambda_{mn}(j))T_{mn}(j) + \delta_{mn}(j)\Delta\lambda_{mn}(j+1) \tag{22}$$

For all $m \in \{1, \ldots\ldots, s\}$ the starting estimation for T can be either randomly selected or calculated from driving cycle. In this propose approaches, at each times instants, the transitions probabilities matrix undergoes updates based on the currents and past driver maximum speed and acceleration. Assuming the driver actions on the gas pedals is modelled as described in (1), the desired references speeds can be determined from the torque requests T_j^{req} and the actual longitudinal speeds v using the following expression:

$$v_{ref} = \frac{T_j^{req}}{k_p} + v \tag{23}$$

Once a transitions probability is determined, the desired speeds profiles can be stochastically generate as a manifestation of the Markov chains.

B. Technical Modelling of New Energy Systems of NEVs

Figure 3 depicts a schematic representation of the new energy vehicles depicting a smart grid connected with various energy production and consumption source. Energy sources consists of solar and wind farms, a thermal power plnt, and residential firms consists of solar panel. Energy consumers include homes, offices, industrial facilities, and EVs. Grids incorporates a segment for "Analysis of Battery Performances," that inline a focus on continuous monitoring EV battery health performances and efficiencies.

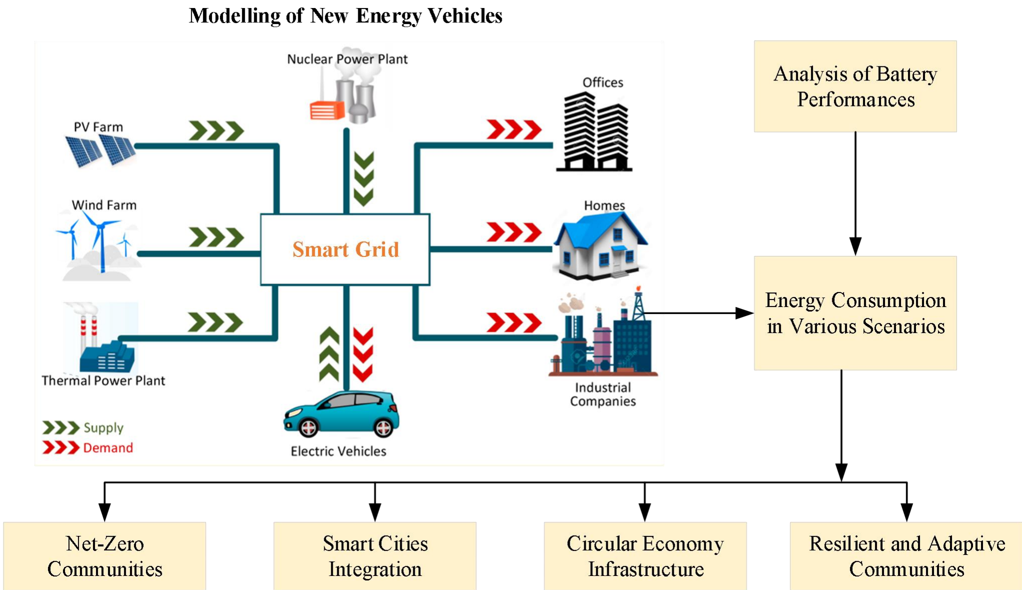

Fig. 3. Technical Modelling of New Energy Vehicles

The core consist of achieving "Net-Zero" emission by advantages of RES like sun and wind to power EVs, thus reducing reliance on fossil fuels and mitigating greenhouse gas emissions. Smart grid technology is positioned to enhancing electricity delivery efficiency, potentially by alignment of generations with demand and small standby power plant operation. This represent comprise of futures where EVs plays an important role in transportation, facilitated by smart grids coordinating electricity flow from various renewable sources.

1) Battery Performance Modelling

Batteries are the primary source of energy consumption in the vehicles. To meet a desired parameter, Diffusion Coefficient it is essential to maintain good airflow while minimizing total power usage. Mathematically, this objective function is described as,

$$P = \sum_{i=1}^{N} V_r \cdot Q_a * \mathrm{t} \qquad \text{Watts} \tag{24}$$

Where, N is the Coulombic Efficiency totally in the batteries, Q_a is the total resistance of batteries from multiple scenarios, Q_a is the sum of rate capability of i, and t is the time required to lessen the polarization in sec. Required power (P_r) for Thermal Runaway Characteristics system is mathematically expressed as in Eq. (25).

$$P_r = R_a \cdot A_q^3 \qquad \text{Watts} \tag{25}$$

Where, R_a is the resistance of the battery system air flow and A_q^3 is the quantity of the air. The value of R_a is related with the changes in the airway roughness value (γ), cross section of the perimeter (ρ), length (τ) and area (A_q).

C. Empirical Data to Validate the Effectiveness of Design Changes

Empirical data confirms the efficiency of given design modification in EVs infrastructure of charging, aimed at augmentation of energy efficiency and user smooth experience. Through a varying method approach, consist quantitative derivation of energy consumption data pre- and post-implementations of the modification, with the comparable evaluations through user satisfaction survey, remarkable improvements were noticed. Validations of the empirical datas illustrate a significant minimization in energy losses during charging sessions subsequent to the design adjustment. User feedbacks denotes a clear improvement in agreement levels related to usability and accessibility of the charging stations. These results highlight the real outcomes of designing measures in improving energy efficiency and user satisfaction within EV charging infrastructures, essential for encouraging widespread EV adoptions and advancing sustainable transportation initiative.

D. Environmental Benefits and Economic Benefits Associated with New Energy Vehicles

In the trend of the EVs there are lot of benefits of including the environmental and the economic benefits are included., In the sense of the environmental analysis, Conventional engine vehicles pollute the atmosphere and brings lot of effects to the environment and leads to ozone layer depletion, pollution of gases etc. In terms of economic analysis, conventional vehicles add lot of cost at initial stage and fueling cost is high compared to conventional mode. But when we switch to electric vehicles, there is no need for refueling, it adds lots of advantages over the conventional one. Analysis related to Economic and Environmental factors are analysed below.

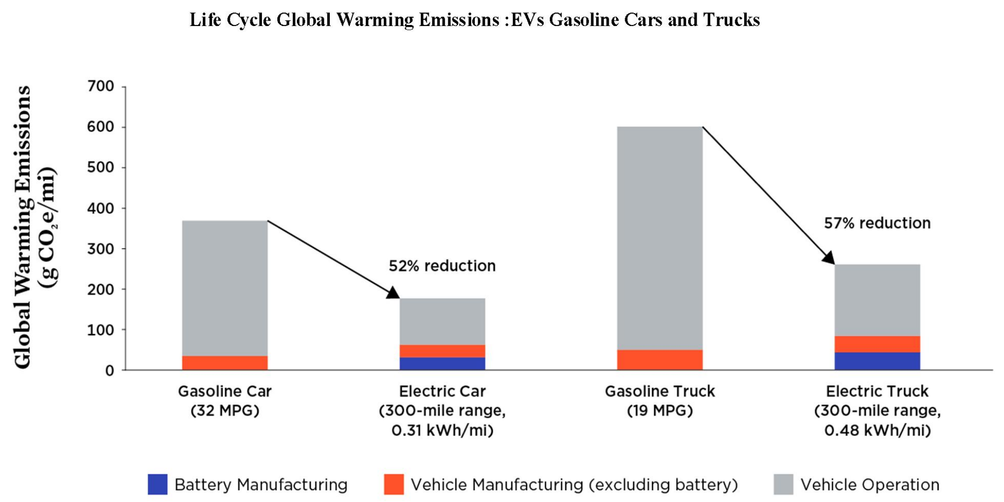

Fig. 4. Environmental Impacts of Usage of Electric Vehicles

Figure 4 shows a bar graph comparing the global warming emissions of EVs and gasoline-powered vehicles in full life time usage. Detailed analysis consists of emission of production, battery production (specifically for EVs), and operation of vehicles.

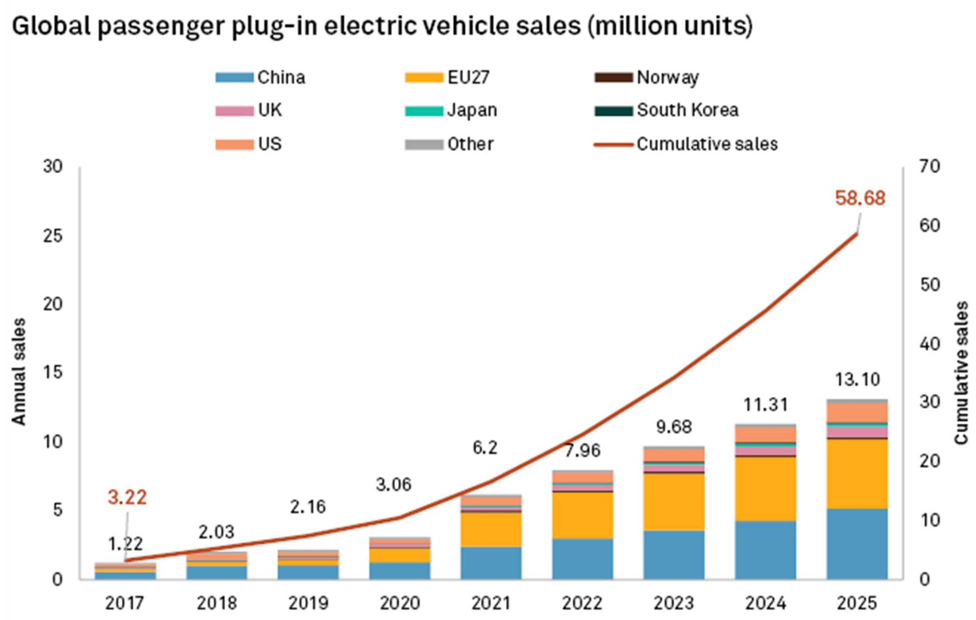

Fig. 5. Sales and Economic Analysis of Electric Vehicles

The figure 5 shows a graph showing global passenger plug-in electric vehicle sales from 2012 to 2025. Sales are measured in millions of units. China is the world leader in sales, followed by Europe (EU27), and the United States. Global sales have grown steadily over the period, reaching nearly 30 million units in 2025.

E. Regulations and Standards Affecting NEV Design and Deployment

Regulations and standard play an important role in making the design and implementation of NEVs. These frameworks comprise of safety, emission, and performance criteria, supporting producers in improving hazardless environment and improved performance vehicles while make sure compliances with legal and government requirement. A semi-structured approach to improving innovation and sustainability in the automotive industry.

1) Power Infrastructure in EV Charging

Figure 6 shows the power infrastructures, which denotes an electric circuits or system enables power exchanges between EVs and the grid. This infrastructure can be classified based on the power type of power utilized, the compilation of charging circuits, physical contact requirements, and the power flow direction.

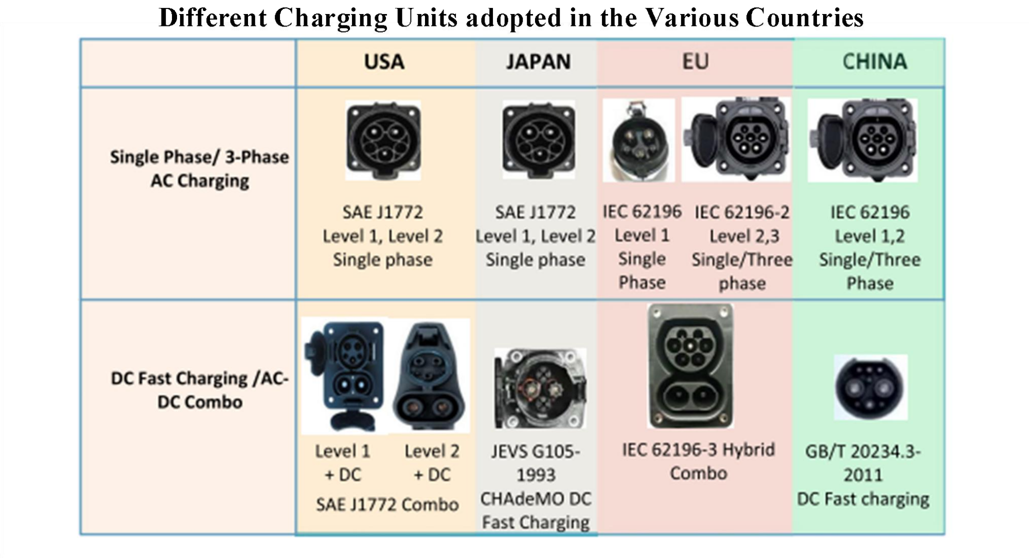

Fig. 6. Various Charging Units Adopted by Different Countries

Figure 6 depicts the various charging adapters used by the different countries and it needs to be uniquely fixed throughout. It needs lot of serious regulations over there and even charging adapters should be implemented all over the world. The charging infrastructure is VITAL for the widespread adoptions of EVs. There is multiple charging standard in the markets, such as CHAdeMOs, CCSE, and Tesla Supercharger. Standards entities such as the IEC and SAE have formulated standard to ensuring the maximum safety and interoperability's of EV charging system. These standards cover the safety of charging equipment's, safety of electrical systems, communication protocol, and the designing and installations of charging station.

2) Control Architecture in EV Charging

The control structures of EV charging involve the distribution grids, the EV charging's stations and EVs, and can be slitted according to the mobilities, coordination's and the control structures.

a) Vehicle Mobility Consideration

In this aspect, EV charging infrastructures can be classified into statics and dynamic chargings. In static charging, the vehicle is considered to be parked in a charging station while chargings. On the contrary, dynamics or mobility aware charging schemes considers different temporal movements, such as vehicle arrivals and departure times, trip history of trip and any unplanned occasions of EV arrival/departures, which is more realistic due to the consideration of spatiotemporal relation of EVs but is more complex and needed advanced infrastructure controls.

b) Charging Coordination

In this aspect, EV charging follows two methods: uncoordinated and coordinated charging control. The uncoordinated charging means that EV batteries either start charging immediately when plugged in or start after a user-adjustable fixed delay and continue the charging until they are fully charged or disconnected.

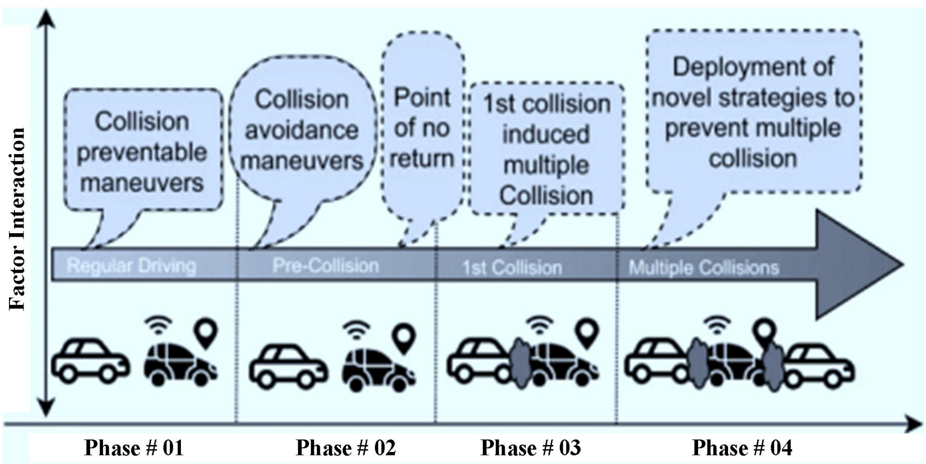

Fig. 7. Implementation of Safety Regulations in Vehicles

Figure 7 depicts the implementation of the safety regulations in the electric vehicles, safety is primary focus in any automobiles, in case of the electric vehicles it should primarily focus on the li-ion batteries and controls of the vehicles., Anticollision system should be implemented to avoid big Collison and for the enhancement of the safety of the vehicles.

5. Results and Discussion

A. Case Studies

The depicted case study focuses on a compact urban neighborhood situated in Mumbai, India. Within this area, there are 11 apartment buildings accommodating a total of 254 residential buildings and 612 residents. Each apartment is reserved one parking spots, total of 417 parking spaces available, all equipped with a wintertime preheating system. The minimum-voltage grid infrastructure serving the neighborhoods consist two 31/0.5 kV substations, each with an annual maximum power capacities of around 400 kW, tallying approximately 600 kW for both substations. 11 residential building are warmed using centralized heating during winter seasons, transferring the impact of outside temperature differences on electricity usages. Furthermore, the nearest layouts, characterized by a last end road with no -traffic, conducting traffic measurements is beneficial for end users.

To illustrate the application of the forecasting methodologies, a traffic survey was conducted over the span of a month. In this study, vehicle kilometers traveled by cars are estimated using the Indian National Travel Survey (INTS), assuming electric vehicles (EVs) or plug-in hybrid electric vehicles (PHEVs) with high-capacity batteries. Charging losses are disregarded, with energy consumption slightly overestimated to compensate. Average daily distribution of cars entering and leaving the area, with distinct peaks coinciding with typical working hours. Enhancing the accuracy of forecast, it's suggested that the survey period be extended beyond the month considered here, ideally to include more workdays. Conducting further travel surveys or employing GPS trackers in vehicles could provide exact Datas on trip length and timing. Survey indicates an average of 84 km/day traveled by car in India. The energy consumption of EVs (and PHEVs when driven with electricity) is assumed to be 0.3 kWh/km, a common estimate in Asian countries.

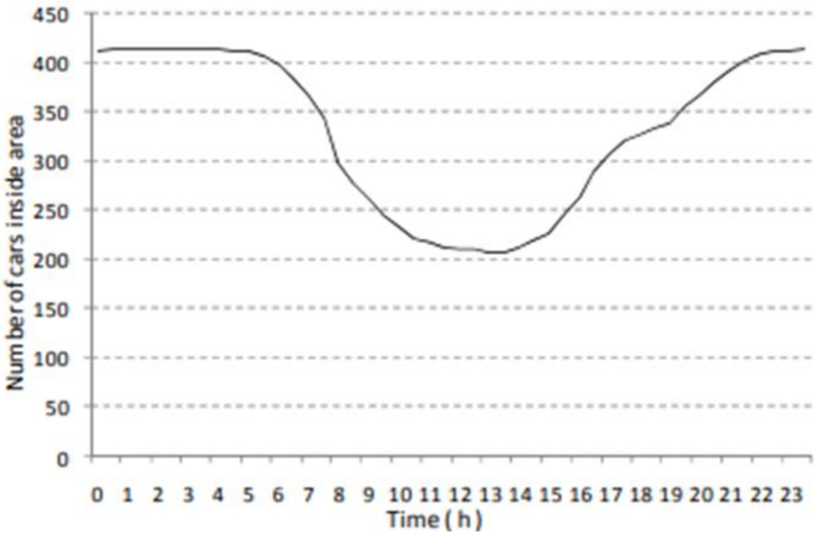

Fig. 8. Estimation of Car Numbers in the Case Area Based on Actual Traffic Flow Measurements

Comparing traffic measurement results (Figure. 3) with NTS data reveals discrepancies; however, the collected data suffice for demonstration purposes and estimation of total energy and charging overlaps. Despite limitations such as the inability to identify individual cars, the data provide insights into total energy usage and charging demands.. Trip lengths, primarily short with some longer journeys, are fitted to a Weibull distribution, as demonstrated in Fig. 8.

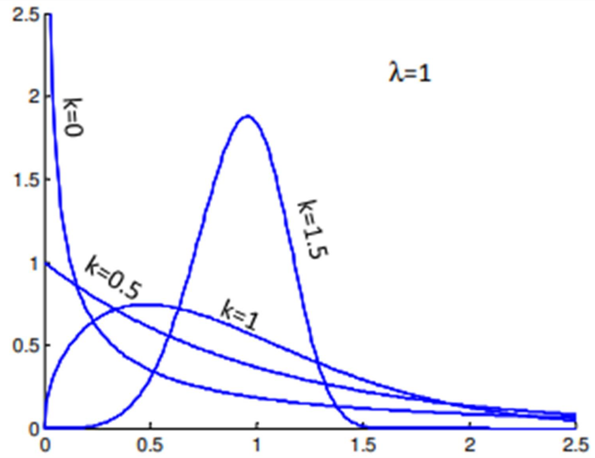

Fig. 9. Case Study Analysis Using Weibull function

In Figure 9, the combined base load and electric vehicle (EV) charging load are illustrated. It's evident that the peak load power experiences a significant increase even at low penetration levels. Figure 10 shows the base load and EV charging load during workdays at a 25% penetration level.

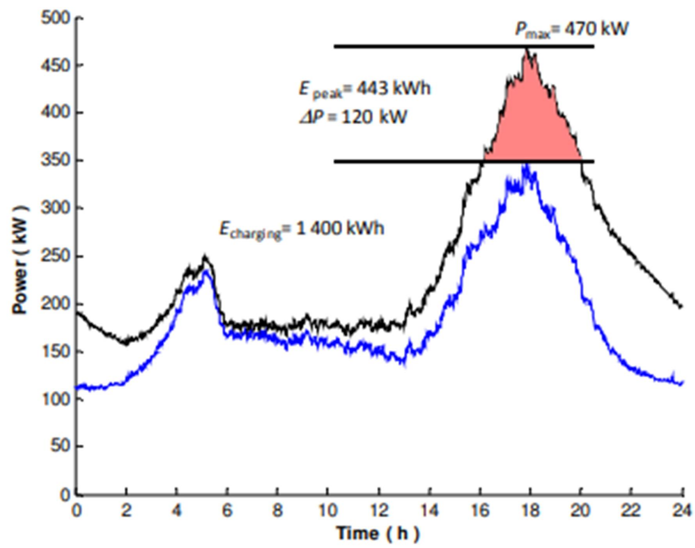

Fig. 10. Base Load and EV Charging Load During Workdays at a 25% Penetration Level

B. Simulation Results

During vehicle interior design, State of Charge (SoC) is a pivotal consideration, dictating the integration of SoC data into the dashboard or infotainment system, the implementation of interactive alerts and notifications based on SoC levels, and the provision of customization options for user preferences regarding SoC display formats.

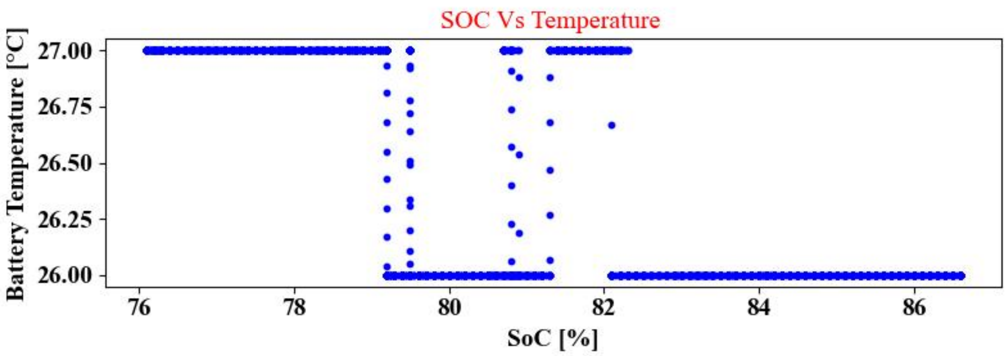

Fig. 11. SoC [%] Vs Temperature

The interior design of a vehicle significantly impacts occupants' comfort and experience. Factors such as seat material, cabin insulation, and HVAC system design play crucial roles in maintaining thermal comfort under varying temperature conditions. Figure 11 illustrates the inverse relationship between SOC and battery temperature in a vehicle. As temperature rises, SOC decreases by 20%, influenced by increased internal resistance, limiting the battery's energy delivery capacity.

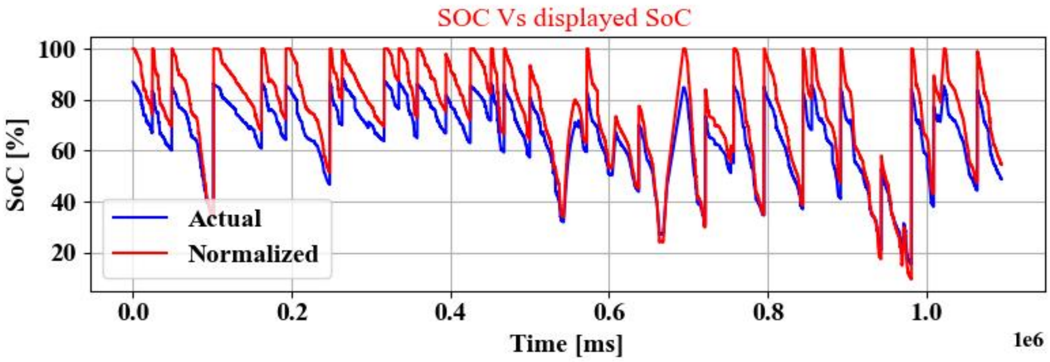

Fig. 12. Displayed SoC [%] Vs Time

The interior designing of a vehicles significantly impacts occupant user comfort and experiences. Factor such as material seat, insulations of cabin, and HVAC systems designing plays dominant roles in maintains thermal stability under different conditions of temperature. Figure 12 shows the relationship between the SoC and voltages in a Li-Ion battery, showcase a gradual decrease in voltage as SOC minimizes. This fall represents the movements of lithium ions within the batteries during the phase of discharge. The table shows a substantial 1-volt reductions in battery voltage as SOC decrease from 100% to 0%.

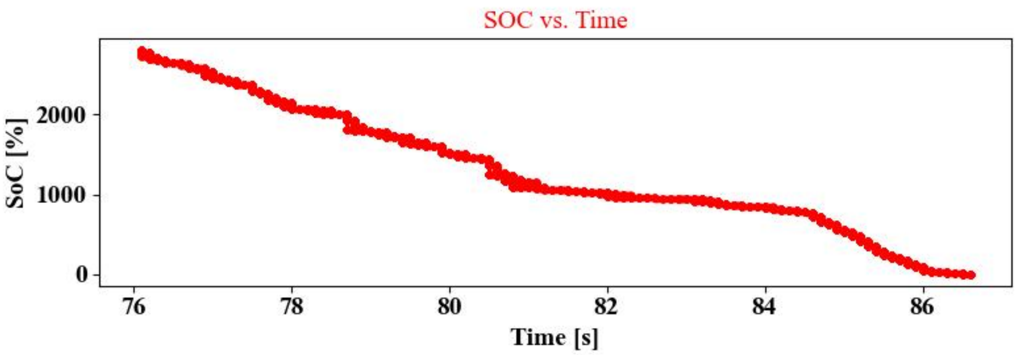

Fig. 13. Displayed SoC [%] Vs Time

The Figure 13 significance of Interior Design of Vehicles, powers the electric motors, exhibiting a consistent 1-volt minimizing in voltages as the SoC falls from 100% to 0%. This voltage reductions stemming from the movements of lithium ion during discharging, impacts the batteries potential. A minimum SOC or voltage corresponding to diminishing mileages, emphasizing the need for extensive considerations of these factors for exact predictions.

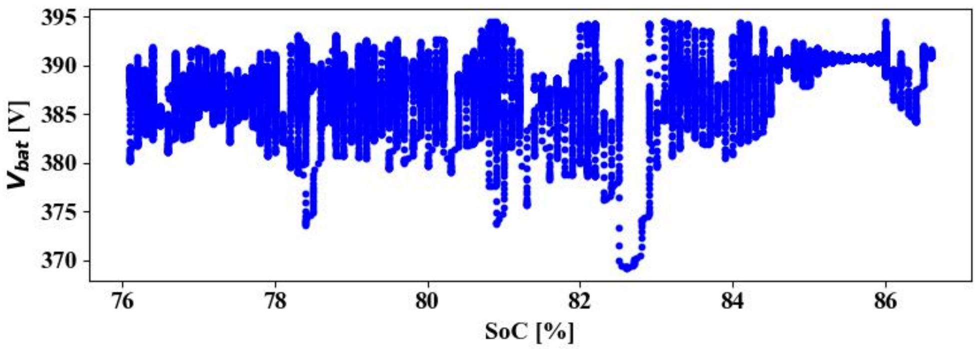

Fig. 14. Performance Analysis of Vbat [V] V/s SoC [%]

The Figure 14 shows a 40% minimizing in the mileage of a battery vehicles as the State of Charges (SOC) decline from 100% to 0% because it shows that there is a minimum in the Interior Designs. This minimizing is attributes to the lowering energy available to power the vehicles. A lower SOC corresponds to impacts to the interior designing of the vehicles, signifies the urgent need for a detailed considerations of these important factors for exact prediction.

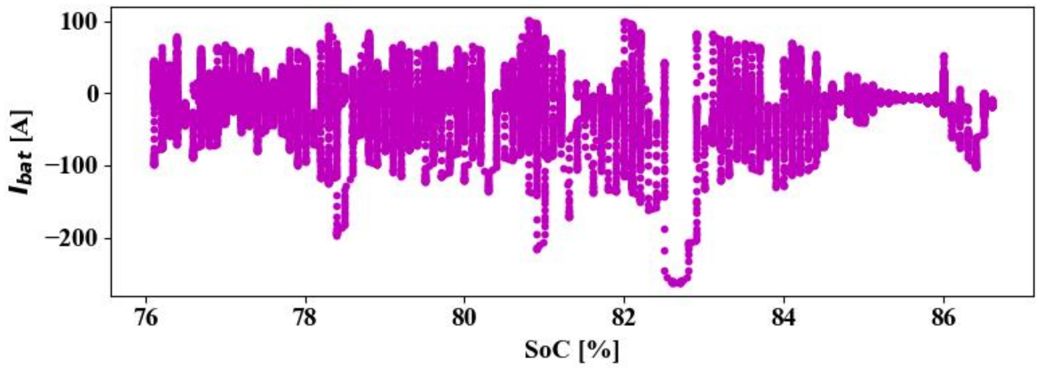

Fig. 15. Performance Analysis of I_{bat}[V] V/s SoC [%]

Figure 15 illustrates the relationship between current of battery (Ibat) and SoC in NEVs. The graph shows that battery current is maximum at minimum SoC level and minimizing as SoC gradually rises, mainly due to efficiency of charging it impacts the interior design. The prediction of mileage in NEVs depends on factors such as SoC, battery capacity, and energy consumption per mile. When the energy consumptions per mile is 300 Wh/mile, the mileage minimize as the SoC increase.

6. Conclusion

In conclusion, this research highlights the importance of SoC as a fundamental designing parameter in the interior design of NEVs within the frameworks of information materializations. By focusing on SoC, the study focuses the deep relationship between management of battery, interactions of user, and overall experiences of users within NEV interiors. The research findings highlights the effectiveness of SoC-driven designing parameters in improving engagement of users, safety, and functionalities. The integrations of SoC datas into NEV interiors must remain a priority, ensuring seamless accessibility, intuitive interpretations and customizable display options to meet the diversifying needs and preference of end users. This research contributes valuable insight to the ongoing research on NEV designs, signifying the importance of complete considerations of energy management aspect in shaping the future of sustainable transportations.

References

[1] D. Jaiswal, V. Kaushal, R. Kant, and P. Kumar Singh, "Consumer adoption intention for electric vehicles: Insights and evidence from Indian sustainable transportation," *Technological Forecasting and Social Change*, vol. 173, Dec. 2021, doi: 10.1016/j.techfore.2021.121089.

[2] K. Laadjal and A. J. M. Cardoso, "Estimation of lithium-ion batteries state-condition in electric vehicle applications: Issues and state of the art," *Electronics*, vol. 10, no. 13, Jun. 2021, doi: 10.3390/electronics10131588.

[3] X. Hu, Z. Deng, X. Lin, Y. Xie, and R. Teodorescu, "Research directions for next-generation battery management solutions in automotive applications," *Renewable and Sustainable Energy Reviews*, vol. 152, Dec. 2021, doi: 10.1016/j.rser.2021.111695.

[4] J. Guo, Y. Li, K. Pedersen, and D. I. Stroe, "Lithium-ion battery operation, degradation, and aging mechanism in electric vehicles: An overview," *Energies*, vol. 14, no. 17, Aug. 2021, doi: 10.3390/en14175220.

[5] N. Noura, L. Boulon, and S. Jemeï, "A review of battery state of health estimation methods: Hybrid electric vehicle challenges," *World Electric Vehicle Journal*, vol. 11, no. 4, Oct. 2020, doi: 10.3390/wevj11040066.

[6] Y. Yoon, C. Kim, J. Lee, and K. Yi, "Interaction-aware probabilistic trajectory prediction of cut-in vehicles using gaussian process for proactive control of autonomous vehicles," *IEEE Access*, vol. 9, pp. 63440-63455, 2021.

[7] U. AlHaddad, A. Basuhail, M. Khemakhem, F. E. Eassa, and K. Jambi, "Towards sustainable energy grids: A machine learning-based ensemble methods approach for outages estimation in extreme weather events," *Sustainability*, vol. 15, no. 16, Aug. 2023, doi: 10.3390/su151612622.

[8] X. Yuan, X. Liu, and J. Zuo, "The development of new energy vehicles for a sustainable future: A review," *Renewable and Sustainable Energy Reviews*, vol. 42, pp. 298-305, Feb. 2015.

[9] H. Gong, M. Q. Wang, and H. Wang, "New energy vehicles in China: policies, demonstration, and progress," *Mitigation and Adaptation Strategies for Global Change*, vol. 18, no. 2, pp. 207-228, Mar. 2012.

[10] Z. Liu, H. Hao, X. Cheng, and F. Zhao, "Critical issues of energy efficient and new energy vehicles development in China," *Energy Policy*, vol. 115, pp. 92-97, Apr. 2018.

[11] D. Siwiak and F. James (Jun. 2009). Designing interior audio cues for hybrid and electric vehicles. *Presented at Audio Engineering Society Conference: 36th International Conference: Automotive Audio*. [Online]. Available: https://aes2.org/publications/elibrary-page/?id=15190

[12] E. Yang, H. J. Ahn, N. H. Kim, H. S. Jung, K. R. Kim, and W. Hwang, "Perceived interior space of motor vehicles based on illusory design elements," *Human Factors and Ergonomics in Manufacturing & Service Industries*, vol. 25, no. 5, pp. 573-584, Jun. 2014.

[13] M. Reed, R. W. Roe, M. A. Manary, C. A. C. Flannagan, and L. W. Schneider, "New concepts in vehicle interior

design using ASPECT," *SAE Technical Paper Series*, Mar. 1999, doi: 10.4271/1999-01-0967.

[14] J. Y. Kwon and D. Y. Ju, "Interior design of fully autonomous vehicle for emotional experience: Focused on consumer's consciousness toward in-vehicle activity," *Korean Society for Emotion and Sensibility*, vol. 21, no. 1, pp. 17-34, Mar. 2018.

[15] A. Mazloumi and F. Mohammadreze, "Ergonomic evaluation of interior design of Shoka vehicle and proposing recommendations for improvement," *Work*, vol. 41, pp. 1477-1485, 2012.

[16] J. F. Petiot, C. Salvo, I. Hossoy, P. Y. Papalambros, and R. Gonzalez, "A cross-cultural study of users' craftsmanship perceptions in vehicle interior design," *International Journal of Product Development*, vol. 7, no. 1/2, p. 28, 2009.

[17] Y. Li, F. Liu, and R. Hao, "Scenario demand-based design of new energy vehicles from the inside out and its practices," *Journal of Physics: Conference Series*, vol. 2235, no. 1, May 2022, doi: 10.1088/1742-6596/2235/1/012081.

[18] S. Li et al., "Proactive human-robot collaboration: Mutual-cognitive, predictable, and self-organising perspectives," *Robotics and Computer-Integrated Manufacturing*, vol. 81, Jun. 2023, doi: 10.1016/j.rcim.2022.102510.

[19] S. Sarkar, A. Pramanik, J. Maiti, and G. Reniers, "Predicting and analyzing injury severity: A machine learning-based approach using class-imbalanced proactive and reactive data," *Safety Science*, vol. 125, May 2020, doi: 10.1016/j.ssci.2020.104616.

[20] E. H. Houssein, N. A. Samee, N. F. Mahmoud, and K. Hussain, "Dynamic coati optimization algorithm for biomedical classification tasks," *Computers in Biology and Medicine*, vol. 164, Sep. 2023, doi: 10.1016/j.compbiomed.2023.107237.

[21] H. M. Hasanien, I. Alsaleh, A. Alassaf, and A. Alateeq, "Enhanced coati optimization algorithm-based optimal power flow including renewable energy uncertainties and electric vehicles," *Energy*, vol. 283, Nov. 2023, doi: 10.1016/j.energy.2023.129069.