User-Centered Optimization of Hybrid Battery/Supercapacitor Storage Systems in Electric Vehicles

Z. Bououchma
Adjunct Professor
Arts et Métiers Institute of Technology
Moulay Ismail University
Morocco

M. El Amine
Associate Professor
Arts et Métiers Institute of Technology
Moulay Ismail University
Morocco

This paper presents a multi-objective optimization approach for designing hybrid energy storage systems combining lithium batteries and supercapacitors in electric vehicles. A desirability-based framework is developed to integrate multiple conflicting objectives, including driving range, system cost, lifetime, and volume occupancy. Each objective is transformed into a normalized satisfaction index using parameterized desirability functions derived from user preferences. These indexes are aggregated into a global performance metric to guide the optimization process. A genetic algorithm is employed to identify optimal configurations that balance trade-offs among objectives. Results demonstrate that the hybrid system significantly improves driving range and lifetime while reducing cost and volume compared to battery-only systems. The proposed method offers a flexible and user-centered design strategy for enhancing electric vehicle performance and reliability.

Keywords: *electric vehicle, hybrid energy storage system, lithium battery, supercapacitor, multi-objective optimization, desirability function.*

1. INTRODUCTION

With the increase of fossil fuel consumption and the crisis of resource shortage, the use of electrical energy has become a priority for major industries such as the automotive industry[1]. Electric vehicles (EVs) and hybrids (HEVs) are the best solutions to cope with climate change which require storage devices like battery and supercapacitors (SC) [2]. In order to have better energy efficiency, the association of batteries with supercapacitors is essential[3]. Lithium-ion batteries offer high energy density but suffer from limited driving range and low power density, these disadvantages can be reduced by inserting a new, reliable energy source capable of supplying power peaks at the right time [4]. Supercapacitors, given their long lifetime, high power density, and strong ability to charge and discharge quickly [5], are plausible candidates to perform this function [6,7]. The combination of batteries and supercapacitors as a second device leads to a significant increase in the EV cost [8].

The primary goal of numerous research efforts is to design and implement an advanced and efficient strategy for optimizing energy management in systems that integrate both batteries and supercapacitors. This involves developing intelligent control algorithms, improving energy distribution between the two storage devices, and maximizing overall system efficiency to enhance performance, extend lifetime, and reduce energy losses [2,6,9].

Optimizing energy consumption in electric vehicles (EVs) is crucial for enhancing efficiency and extending driving range. One effective approach involves implementing economy-oriented car-following control strategies, which adjust the vehicle's speed in response to traffic conditions, thereby reducing energy usage [10, 11].

Additionally, integrating machine learning-based energy optimization systems can dynamically manage factors such as battery state of charge, driving speed, and route characteristics, leading to more efficient energy consumption [10,11].

Furthermore, optimizing the design and control of EV transmissions, including the use of multi-speed gearboxes, can significantly improve energy efficiency by ensuring the electric motor operates within its optimal efficiency range [12].

In addition to these technological advancements, adopting certain driving practices can further enhance EV energy efficiency. Practicing gentle acceleration and maintaining moderate speeds can significantly reduce energy consumption [13].

Utilizing regenerative braking systems allows for the recovery of kinetic energy during deceleration, converting it back into usable energy for the vehicle [14].

By combining advanced technological strategies with mindful driving habits, EV owners can optimize energy usage and contribute to a more sustainable future.

Mid-Eum Choi et al. described an optimization approach based on the multiplicative-increase-additive-decrease (MIAD) to minimize magnitude/fluctuation of the battery current and the energy loss in the hybrid energy storage system. This method results in extended battery life and reduces the size of the battery [2].

Lahyani et al. presented a comparison of the performance of a lead-acid battery/supercapacitors (hybrid) to a battery alone under pulsed loads. This experience shows that using battery/supercapacitors (hybrid) redu–

Received: July 2025, Accepted: September 2025
Correspondence to: Dr Zoubida Bououchma
Arts et Métiers Institute of Technology ,
P.O. Box 4024, Marjane 2 Meknès, Morocco
E-mail: bououchma.zoubida@gmail.com
doi: 10.5937/fme2504575B

ces 36% of power dissipated compared with battery alo–ne, increases the number of cycles by 70%, reduces cost by 17,6%, reduces the battery's capacity fade by 60% and increases of internal resistance by 83% [6].

Riadh et al. studied an optimal use of the complementarity between supercapacitors and batteries in electric vehicles. They integrated a high pass filter on the side of supercapacitors in order to overcome the peak power demands and increase battery lifetime. The result shows that minimizing battery current affects inc–reasing supercapacitors number which is expensive [9].

Chunchun Jia et al. proposed a novel energy mana–gement strategy for hybrid electric buses based on dynamic programming (DP) with the aid of an online self-learning stochastic Markov predictor (OLSMP). This study has given as a result a reduction of 34,8% battery aging rate and low total operating cost (12,3%) compared to the overheat-protection neglecting strategy [1].

With the goal of minimizing the energy consumption of the battery/supercapacitor hybrid energy storage system, Liqiao Lia et al. proposed a new method based on self-adaptive reinforcement learning for Electric Tractor based on working condition identification energy management. This method reduces energy consumption by 15,7% [15].

Ridoy Dasa et al. present in their work optimization method based on multi-objective-techno-economic-environmental for electric batteries, they use energy cost, battery degradation, grid interaction and CO2 emissions. This method reduces the energy cost,battery degradation, CO2 emissions and grid utilisation by 88.2%, 67%, 34% and 90% respectively [16] .

Ziyou Song et al. propose a semi-active hybrid energy storage system (HESS) that integrates a battery with a supercapacitor (SC) using a smaller unidi–rectional DC/DC converter. This configuration aims to enhance system efficiency and reduce costs. The study incorporates a quantitative model to assess battery capacity degradation and focuses on optimizing the sizing parameters of the HESS for an electric city bus in order to minimize both the total cost of the HESS and the capacity loss of a $LiFePO_4$ battery over a typical china bus driving cycle[17].

Despite significant progress in optimizing hybrid bat–tery/supercapacitor systems, most studies focus on tech–nical performance - such as minimizing current fluctua–tions or enhancing cycle life - while neglecting trade-offs among cost, lifetime, and volume, as well as real-world user preferences. Many approaches also rely on complex or costly architectures that limit practical adoption.

To overcome these limitations, this study proposes a user-centered, multi-objective optimization framework that integrates technical metrics with consumer-driven desirability functions. By explicitly incorporating user preferences, the framework balances technical, eco–nomic, and practical considerations, providing a realistic and implementable design strategy for hybrid energy storage systems in electric vehicles.

The remainder of this paper is organized as follows. Section 2 presents various energy storage architectures for electric vehicles and justifies the selection of the chosen hybrid configuration. Section 3 details the multi-objective optimization model, including the formulation of the global satisfaction index based on user prefe–rences and desirability functions. It also describes the modellingof key performance criteria such as driving range, system cost, lifetime, and volume occupancy. Section 4 outlines the optimization procedure used to identify the best energy storage configuration. Section 5 discusses the simulation results and highlights the benefits of the hybrid storage system compared to a battery-only solution. Finally, Section 6 summarizes the main conclusions and suggests directions for future research.

2. STORAGE ENERGY ARCHITECTURE IN ELECTRIC VEHICLE

Different storage energy architectures have been con–sidered in the literature. The choice between these architectures is based on the trade-offs between comp–lexity, design cost, and performance [18,19].

Several parallel configurations exist, architecture without converter, architecture with converter on the supercapacitor side and architecture with two converters

Table 1 below summarizes the advantages and dis–advantages of each architecture.

Table 1. Comparison of association architectures[19]

Architectures	Simplicity of implementation	Performance	Flexibility	Cost
architecture without converter	+ +	-	-	+ +
architecture with one converter	+ -	+ -	+ -	+ -
architecture with two converters	-	+ +	+ +	-

+Advantages - Disadvantages

Using DC/AC converters for all the architectures (parallel or series), allows adaptation of the voltage of the DC bus to the alternating current electrical machine of the vehicle [19].

The architecture with two DC/DC converters linked to each source (supercapacitors, battery) shown in Figure 1 offers the best performance longer battery life, efficient regenerative braking, and power flow control, however, this configuration involves high cost and imp–lementation complexity.

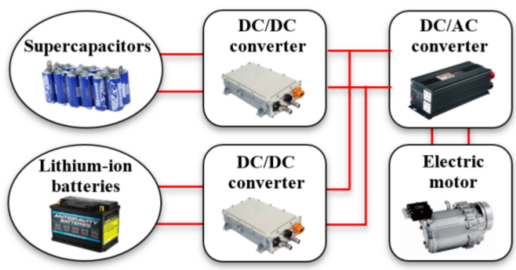

Figure 1. Parallel architecture with two converters

In our article, we have chosen the architecture with two converters despite its drawbacks in terms of cost and implementation complexity. This decision was made with the aim of fully leveraging the flexibility and performance offered by this configuration. By optimizing its operation, we aim to compensate for its inherent disadvantages through improvements in the overall "lifecycle cost" of the system.

3. OBJECTIVE FUNCTION

In this section, the optimization problem is presented, this global control formulation requires the specification of an objective function in order to obtain the best energetic and economic configuration.

In the present study, we aim to improve several design objectives: driving range, cost, lifetime, and volume occupancy.

These objectives are conflicting, meaning that improving one may lead to the deterioration of another.

For example, increasing the driving range requires additional battery cells, which in turn raises the cost. As a result, it is difficult to optimize all objectives simultaneously. To address this challenge, we adopted an aggregation-based approach. Instead of optimizing each objective individually, this method combines multiple objectives into a single function, referred to as the Global Satisfaction Index (GSI), which quantifies the global satisfaction level of a design solution. The overall methodology used to construct the GSI objective function is illustrated in Figure 2.

Starting from a specified energy storage confi–guration (defined by a given number of battery cells and supercapacitor modules), calculation models are first used to derive performance values, denoted as p_i. Each design objective is associated with a specific perfor–mance index. For example, the objective "Improving range" corresponds to the performance index "Range," expressed in kilometers. Accordingly, each performance value (p_1, p_2, p_3 and p_4) is linked to a dedicated calculation model, as detailed in the sections below.

Next, for each performance index, a desirability index (z_1, z_2, z_3 and z_4) ranging from 0 to 10 is assigned to reflect the degree of satisfaction related to the corresponding design objective [20]. In our approach, this mapping is achieved using an adjustable desirability function originally introduced by Harrington [21]. This desirability function is easily parameterized to reflect the preferences of the decision-maker. As shown in Figure 3, only two reference points are required to define each desirability function.

To ensure that these functions accurately reflect user expectations, a structured survey was conducted among potential electric vehicle users.

Given that the present case study focuses on an urban electric vehicle, we specifically targeted urban EV users. Respondents were asked to assess the im–portance and acceptability of various performance metrics, enabling us to calibrate the shape and thres–holds of thedesirability functions used in the opti–mization model. Table 2 summarizes the values obtained from the survey.

Finally, the Global Satisfaction Index (GSI) is obtained by aggregating the satisfaction indexes (z_1, z_2, z_3, and z_4) corresponding to each design objective. As shown in Figure 3, the aggregation function used is the weighted product. The main reason for choosing this function is that it satisfies the principle of annihilation [22], one of the fundamental axioms of design-ready aggregation models [23]. This principle states that if any attribute reaches its worst possible value (a satisfaction index equal to zero in our case), the overall evaluation (GSI) is entirely determined by that attribute, regardless of the others. This ensures that critical failures dominate the assessment. In contrast, the weighted arithmetic mean — one of the most commonly used aggregation functions — does not satisfy this principle, as it can yield a non-zero GSI even when one of the satisfaction indexes (z_1, z_2, z_3, or z_4) is zero. The four weights (w_1, w_2, w_3, or w_4) in the aggregation function represent the relative importance assigned to each design objective. To ensure alignment with user preferences, these weights were derived from the data collected through the aforementioned survey. Table 2 summarizes the values obtained from the survey.

Table 2. Weight values and Harrington function parameters derived from the survey

Design objectives	Harrington function parameters				Weight values
	Point A		Point B		
	p_i	z_i	p_i	z_i	
Improving range	200 Km	4.2	400 Km	8.4	0.37
Reducing cost	2000 €	8.9	4000 €	3.1	0.31
Improving lifetime	30 000 hours	3.9	50 000 hours	6.5	0.21
Reducing volume occupancy	50 litre	6.7	70 litre	5.1	0.11

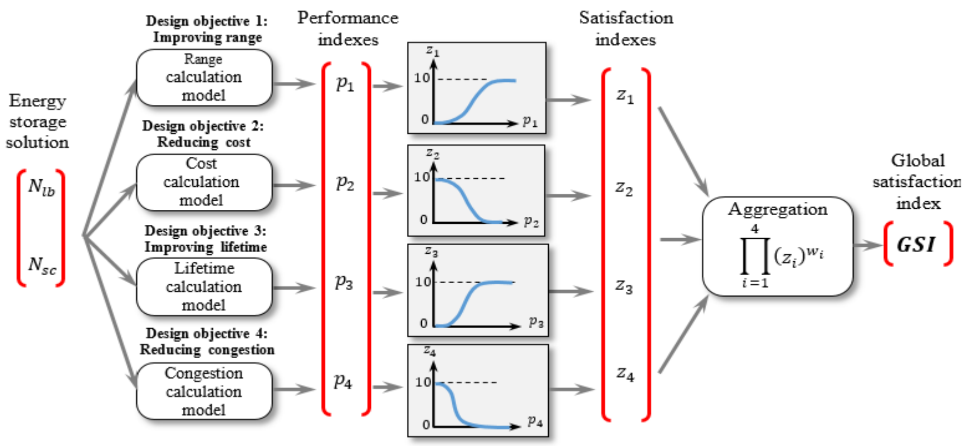

Figure 2. Model Used to Obtain Global Satisfaction Index

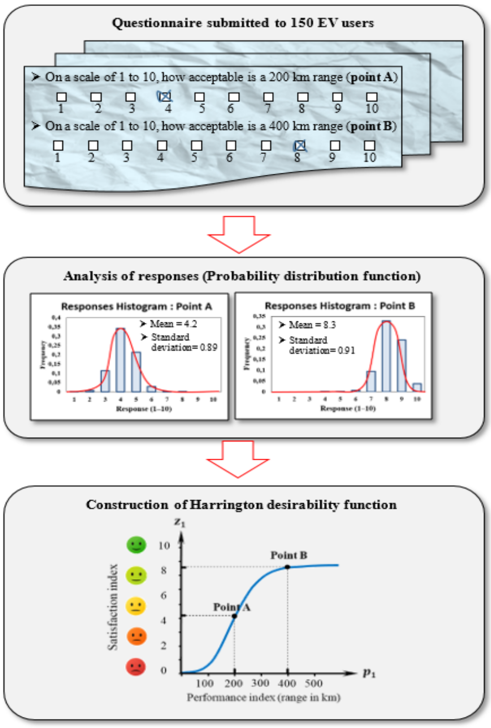

Figure 3. Parametrization of Harrington desirability functions based on consumers' preferences (example of driving range)

2.1 Driving range model

Driving range constitutes a key factor in the adoption and development of electric vehicles (EVs), as it reduces range anxiety, boosts user confidence, and increases their competitiveness with conventional vehicles. It also drives innovation in battery technology and power management, contributing to improved performance and lower costs. For these reasons, driving range is a central design objective in our optimization process.

In this section, we detail the procedure used to esti–mate the driving range for a given energy storage system. The method is based on a simulation of energy exchanges between the powertrain and the storage components. Starting from a fully charged storage system, the aim is to determinethe maximum driving time (in hours) before the storage system is depleted. Figure 4 presents a flowchart of the procedure used to calculate the driving range of electric vehicles. Initially, the driving time (denoted Td) is set to zero, and the battery is considered fully charged. Then, Td is incre–mented by a time step (denoted ΔT) of 1 second at each iteration. At each step, the state of charge of the storage system is updated by computing the energy flux between the battery, the supercapacitors, and the motor. The energy flux is determined based on the instan–taneous power demand, the state of charge, and the energy management strategy (as described in Figure 5). The iterations continue until the battery is fully dis–charged. At that point, the driving range is defined as the final value of Td reached before the storage system is depleted.

As mentioned in Figure4, at each iteration, the energy flux between batteries, SCs and engine is assessed based on the energy management strategy presented in Figure 5. This allows the actualization of storage system state.

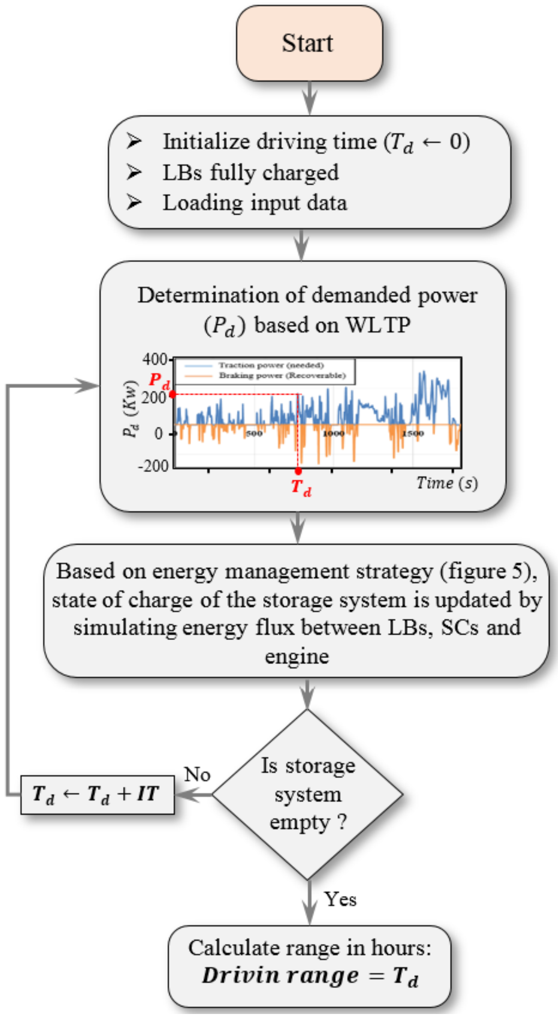

Figure 4. Flowchart of the driving range calculation procedure

At each time step i, the state of charge (SoC) of the hybrid storage system—composed of lithium batteries (LBs) and super-capacitors (SCs)—is updated based on an energy management strategy that distinguishes between traction and braking modes. The demanded power is determined according to a predefined driving cycle (WLTP in our case), and the system identifies whether the vehicle is in braking or traction mode. During braking, the recovered energy is used to recharge the storage devices. In traction mode, the system compares the demanded power P_{lb} with the maximum deliverable power by the lithium batteries P_{lb}. If $P_d \leq P_{lb}$, only the batteries are used. Otherwise, the SCs are activated to supplement the LBs. The energy contri–butions and extractions from each component are com–puted every second, taking into account inverter effi–ciency η, and the SoC of each storage unit is updated accordingly. This real-time control allows the system to balance performance and efficiency while preserving battery health. Figure 6 shows the instantaneous traction and regenerative braking power profiles derived from the Worldwide Harmonized Light Vehicles Test Procedure (WLTP), based on the time-dependent speed input.

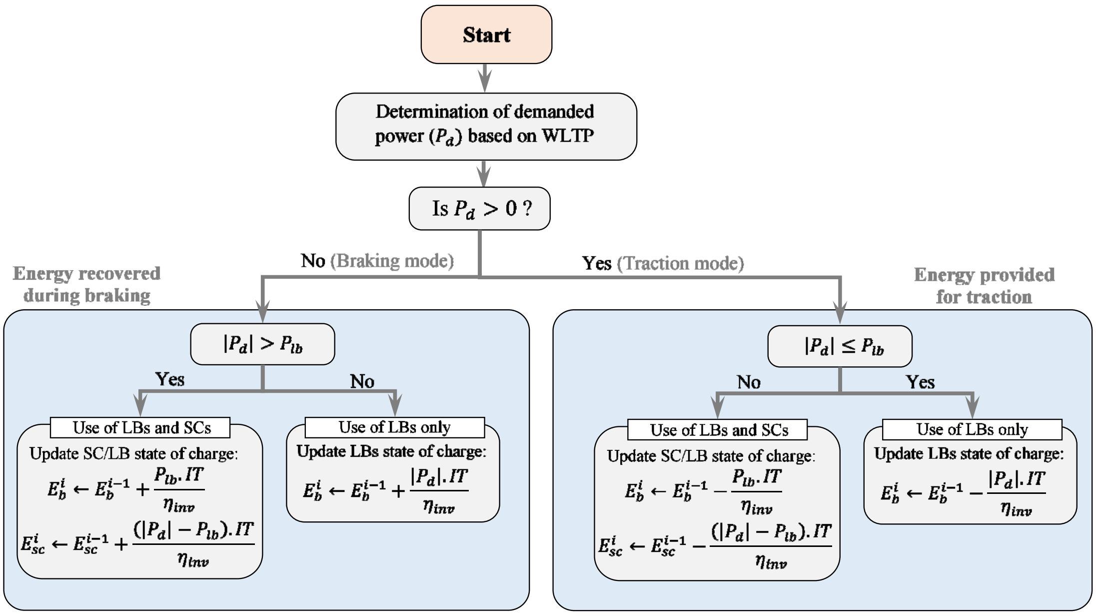

Figure 5. Energy management strategy for updating the state of charge of the storage system at time *i*

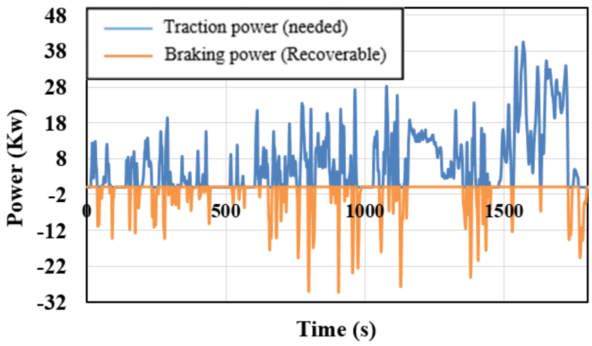

Figure 6. Instantaneous traction and regenerative braking power profiles during the WLTP driving cycle

2.2 Cost model

The first and fundamental objective that we need to mini–mize is the energy cost, the net present cost (NPC) which includes the capital cost (CC), maintenance cost (MC) and replacement cost (RC) of the storage system [24].

$$NPC = N_{sc} \cdot P_{ns} \cdot \left(CC_s + PWA_s \cdot MC_s + K_s \cdot RC_s\right) + \\ + N_{lb} \cdot P_{nb} \cdot \left(CC_b + PWA_b \cdot MC_b + K_b \cdot RC_b\right) \tag{1}$$

where

K_b and K_b are coefficients used to convert the replacement cost of LB and SC at the end of its life into current costit's calculated as[25]:

$$K = \sum_{n=1}^{l_1} \frac{1}{\left(1+i_r\right)^{n \cdot i_2}} \tag{2}$$

PWA_s, $PWA_b$are coefficients used to estimate the current maintenance cost of (LB and SC), it's calculated as:

$$PWA = \frac{\left(1+i_r\right)^R - 1}{i_r\left(1+i_r\right)^R} \tag{3}$$

l_1, l_2, i_r, R are respectively the number of replacement times, component lifetime, the interest rate and project lifetime.

2.3 Lifetime model

In this work, the lithium-ion battery lifetime is estimated based solely on cycle aging, which is the dominant degradation mechanism in electric vehicle applications [26-28]. The cycle aging is quantified through the concept of equivalent full cycles (EFC), computed from the depth of discharge (DoD) and the charge throughput [29]. At each time step, the current drawn from the battery is estimated using the instan–taneous power and voltage:

$$I_{bat}(t) = \frac{P_{bat}(t)}{V_{bat}(t)} \tag{4}$$

The exchanged charge over a time step Δt is given by:

$$\Delta Q(t) = I_{bat}(t) \cdot \Delta t \tag{5}$$

The total number of equivalent full cycles is accu–mulated by summing the charge exchanged over time and normalizing by twice the nominal capacity:

$$N_{eq} = \sum_i \frac{\left|\Delta Q(i)\right|}{2 \cdot Q_{nom}} \tag{6}$$

Finally, the end-of-life (EoL) is defined when the accumulated number of cycles reaches the manu–facturer-specified limit N_{max}, corresponding to a rema–ining capacity of 80%:

$$N_{eq} \geq N_{\max} \tag{7}$$

This approach enables battery degradation prediction under real driving profiles using simulation data, and can be easily extended to include temperature and DoD-dependent degradation models.

Although the same mathematical expression for equivalent full cycles is used for both lithium-ion batteries and supercapacitors, the underlying aging mechanisms differ significantly. Battery degradation is highly dependent on depth of discharge, C-rate, and temperature, often requiring non-linear modeling. In contrast, supercapacitor aging is primarily driven by the total number of cycles and the maximum voltage applied, which allows for a more linear approximation. Therefore, while the same cycle-counting formula facilitates unified simulation, it should be interpreted differently for each storage technology.

2.4 Volume occupancy model

The Volume Occupancy in electric vehicles represents the relationship between energy density (ρ), power density (E), and occupied volume (V).

$$V = \frac{E_{tot}}{\rho_E}. \tag{8}$$

Lithium-ion (Li-ion) batteries are widely used due to their high energy density, they can store a large amount of energy in a small volume.

Supercapacitors provide high power density but have a lower energy density than Li-ion batteries.

4. OPTIMIZATION PROCEDURE

In this study, we adopted a structured and exhaustive optimization strategy based on a Design of Experiments (DoE) approach to determine the optimal configuration of the hybrid energy storage system. Given the limited and discrete nature of the decision variables - namely, the number of lithium-ion battery and supercapacitor units - a full-factorial experimental design was feasible and implemented.

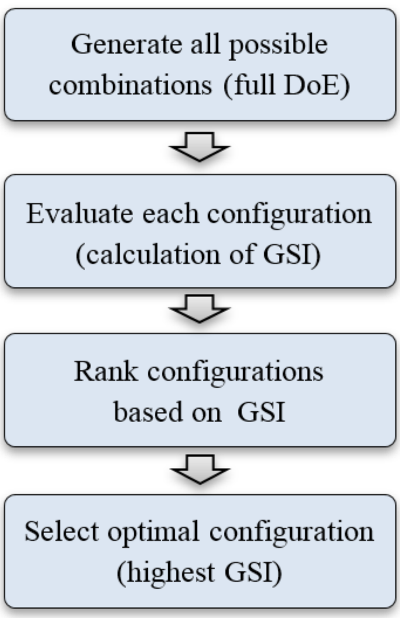

Figure 7. Optimization procedure of energy storage system using genetic algorithm

This allowed us to systematically evaluate all pos–sible configurations within the design space. Although no filtering was applied to eliminate suboptimal solutions a priori, the method remained computationally tractable due to the manageable number of combi–nations. The transparency, reproducibility, and exhaus–tive nature of the approach make it particularly well suited to engineering design problems, where global optimality and interpretability are essential.

5. DISCUSSION OF OBTAINED RESULTS

This section presents the results obtained from the simulation using the Maxwell supercapacitor model and LG Chem E63 lithium-ion batteries. Both components were modelled based on their respective technical specifications, enabling a detailed evaluation of the dynamic performance of the hybrid energy storage system. The analysis focuses on the impact of the selected architecture on power profiles and the energy distribution between the two sources.

The optimization results confirm the effectiveness of the proposed desirability-based multi-objective frame–work in identifying [30] well-balanced energy storage configurations for electric vehicles (EVs). By integrating four conflicting design objectives - driving range, system cost, lifetime, and volume occupancy - into a single Global Satisfaction Index (GSI), the methodology enabled a comprehensive exploration of trade-offs and led to optimal configurations aligned with user preferences.

Table 3. Characteristics of optimal storage system

Criterion	Battery-only System	Optimized Hybrid System	Improve-ment (%)
Driving Range(km)	180	240	+33.3%
Total Cost (€)	4200	3600	−14.3%
Lifetime (hours)	28 000	41 000	+46.4%
Volume Occupancy(l)	62	55	−11.3%
GSI Score	0.58	0.82	+41.4%

The Pareto-optimal configurations identified using the genetic algorithm provide valuable insights into the interactions between thedesign objectives. For instance, configurations optimized for extended driving range tend to include more battery cells, which raises both cost and volume. In contrast, configurations favoring extended system lifetime typically rely more on supercapacitors (SCs), which efficiently manage peak power demands and reduce battery stress. However, this increase in SCs leads to higher volume occupancy, slightly impacting the volume occupancyindex.

The desirability functions, calibrated using feedback from 150 urban EV users, played a pivotal role in shaping the optimization outcomes. The weights derived from survey responses indicate that users prioritize driving range (0.37) and cost (0.31) over lifetime (0.21) (0.11). This preference structure explains why the optimal configurations slightly favor longer range and lower cost, even when lifetime or compactness could be marginally improved.

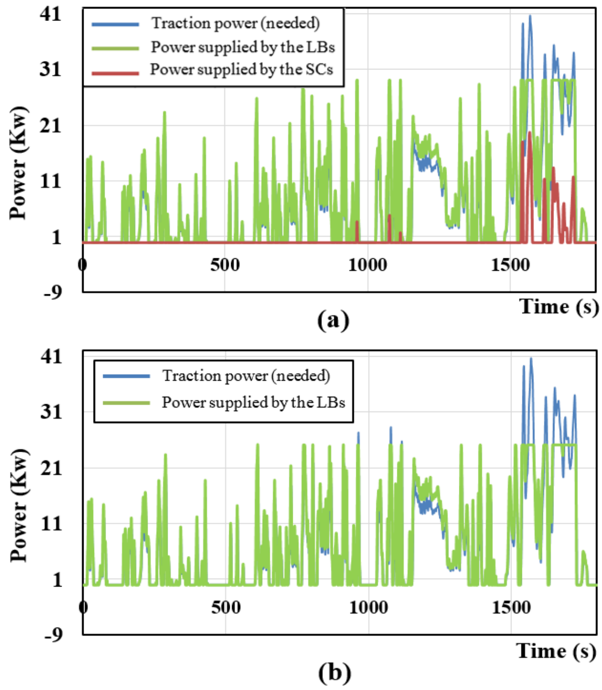

Figure 7. Comparison of power distribution in two optimal energy storage systems during a driving cycle: (a) Hybrid system with lithium batteries (LBs) and supercapacitors (SCs); (b) System with lithium batteries only.

Figure 7 compares power distribution during a standard driving cycle. In the hybrid configuration (Figure 7a), SCs absorb and deliver high peak power during acceleration and braking events, thereby reducing power transients handled by the lithium batteries. This buffering effect stabilizes battery load, leading to improved lifetime and reduced thermal stress. In contrast, the battery-only system (Figure 7b) handles all power variations directly, which increases electrochemical stress and accelerates battery aging mechanisms such as capacity fade or lithium plating.

From an energy management perspective, the hybrid system enhances round-trip efficiency by leveraging the fast charge-discharge capabilities of SCs. It also reduces the depth and rate of discharge of batteries, which positively impacts battery life and system reliability—key metrics in EV design.

Figure 8 (a) illustrates the comparison between the recoverable braking power and the actual power absorbed by lithium batteries (LBs). The results show that although the recoverable braking power exhibits several peaks of high intensity, the power recovered by the LBs remains limited. This limitation is mainly due to the intrinsic characteristics of LBs, such as their relatively low power density and restricted charge acceptance capability during rapid transient events. As a result, a significant portion of the available braking energy cannot be effectively captured, particularly during short-duration, high-power peaks.

In contrast, Figure 8 (b) presents the case of a hybrid storage system combining LBs and supercapacitors (SCs). The addition of SCs, represented by the red curve, enables the system to better follow the recoverable braking power profile. SCs absorb the sharp and high-power transients that exceed the capacity of the LBs, while the LBs handle the lower and more sustained portions of the recovered energy. This comp–lementary behavior between LBs and SCs leads to a higher energy recovery efficiency and alleviates stress on the LBs by reducing their exposure to high-power fluctuations. Consequently, the hybrid configuration de–monstrates superior performance compared to a battery-only solution, highlighting the advantage of integrating SCs into regenerative braking energy recovery systems.

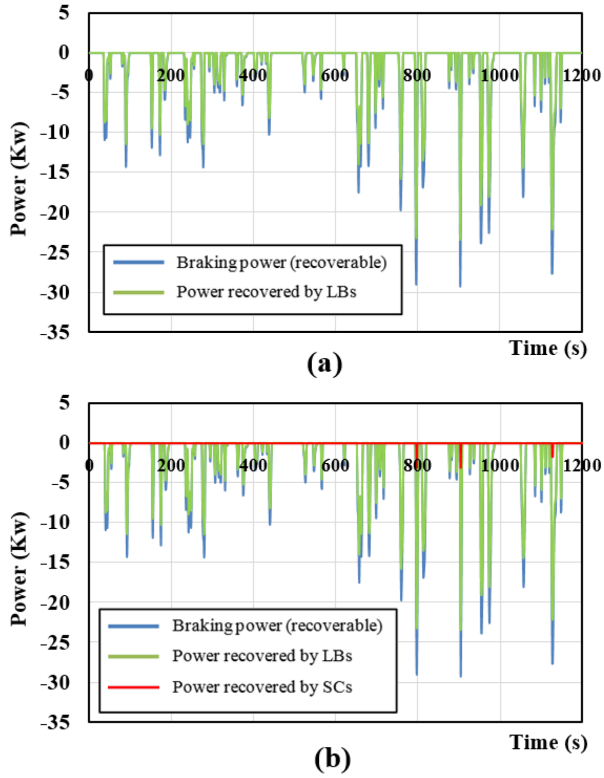

Figure 8. Comparison of regenerative braking power distribution for two optimal energy storage systems: (a) Hybrid system with lithium batteries (LBs) only; (b) System with lithium batteries (LBs) only and supercapacitors (SCs).

It is also important to note that part of the gap bet–ween recoverable and actually recovered braking energy is due to conversion losses and storage inefficiencies, which are inherent to lithium battery chemistry and associated power electronics.

From a technological standpoint, the optimized hybrid configuration demonstrates significant advan–tages over traditional designs:

- Lower lifecycle cost due to better sizing and reduced replacements.
- Increased operational lifetime thanks to smoother battery loads.
- More efficient space utilization, though volume remains a secondary objective.

The weighted product aggregation function used in the GSI ensures that critical shortcomings (e.g., excessively low range or high cost) are not compensated by strong performance in other metrics. This strictness enhances the robustness and practicality of the optimization outcomes for real-world deployment.

Finally, although the current results are promising, their relevance depends on the driving context. For more aggressive profiles, the role of SCs could become more prominent, especially regarding regenerative braking and high-power transients. This highlights the importance of adapting the optimization framework to a variety of use cases and real driving patterns.

Overall, the proposed framework offers a robust, user-centred, and computationally efficient tool for hybrid energy storage system design, with potential for extension to electric buses, delivery vehicles, and other smart mobility applications. Beyond the context of urban electric vehicles, this framework can be extended to a wide range of applications, including electric buses, delivery vans, and stationary energy storage systems such as microgrids and renewable energy integration. By explicitly aligning technical design with consumer expectations, the methodology supports faster industrial adoption and market acceptance.

6. CONCLUSION

This study presented a user-centered, multi-objective optimization approach for the design of hybrid energy storage systems that combine lithium-ion batteries and supercapacitors in electric vehicles. By incorporating both technical and user-related aspects, the proposed framework offers a more holistic and practical design methodology. Unlike traditional approaches that focus solely on technical performance metrics, our method integrates consumer preferences into the optimization process through parameterized desirability functions. This allows for a more realistic evaluation of trade-offs between conflicting objectives such as driving range, cost, system lifetime, and volume occupancy.

The results demonstrate that hybrid configurations, when properly sized and optimized, offer clear advan–tages over battery-only systems. Notably, the inclusion of supercapacitors leads to improved battery lifespan and smoother power delivery, while the optimization framework ensures that these gains do not come at the expense of excessive cost or spatial requirements. The use of the Global Satisfaction Index (GSI), based on weighted desirability functions calibrated via user surveys, proved effective in guiding the selection of optimal configurations aligned with real-world expec–tations. Furthermore, the intelligent brute-force search combined with constraint filtering ensured global optimality while maintaining computational feasibility.

Despite the promising outcomes, several aspects re–main open for future exploration. One important direc–tion is to incorporate more advanced degradation models for both batteries and supercapacitors, taking into account factors such as temperature, C-rate varia–bility, and state-of-charge windows. Another promising avenue is the integration of real driving profiles and probabilistic traffic patterns to better reflect urban mobility conditions. Additionally, the current frame–work could be extended to include dynamic recon–figuration strategies, allowing the hybrid system to adapt to changing load demands or driving conditions in real time. Finally, the approach could be applied to other use cases beyond urban electric vehicles, such as electric buses, delivery vans, or microgrid energy storage systems.

Overall, the proposed optimization strategy provides a robust, transparent, and adaptable solution for designing next-generation hybrid storage systems, with strong potential to support the widespread adoption of electric vehicles.

As a perspective for future work, it would be valuable to extend the proposed user-centered, multi-objective optimization framework to explicitly include environmental criteria such as recyclability. In particular, supercapacitors (SC) generally offer higher recyclability than lithium batteries (LB), which could significantly improve the overall sustainability of hybrid energy storage systems in electric vehicles. Incorporating recyclability alongside technical, economic, and user-preference metrics would provide a more comprehensive design strategy that balances performance, cost, lifetime, and environmental impact.

REFERENCES

[1] Jia, C., Zhou, J., He, H., Li, J., Wei, Z., Li, K. and Shi, M.: A novel energy management strategy for hybrid electric bus with fuel cell health and battery thermal and health-constrained awareness, Energy,Vol. 271, pp. 127105, 2023.

[2] Choi, M.E., Kim, S.W., Seo, S.W.: Energy Mana–gement Optimization in a Battery/Supercapacitor Hybrid Energy Storage System, IEEE Trans. Smart Grid,Vol. 3, No. 1, pp. 463-472, 2012.

[3] Bououchma, Z., Sabor, J. « Real-Time Iden–tification of Supercapacitor RC Model Parameters Using Recursive Least Squares Method, in:*2020 IEEE 2nd International Conference on Electronics, Control, Optimization and Computer Science (ICECOCS)*, 2-3.12.2020, Kenitra, pp. 1-6.

[4] Bououchma, Z., Sabor, J.: Comparison Between Recursive Least Squares Method and Kalman Filter for Online Identification of Supercapacitor State of Health, Stat., optim. inf. comput., Vol. 10, No. 1, pp. 119-134, 2022.

[5] Bououchma, Z., Sabor,J., Aitbouh, H.: New elec–trical model of supercapacitors for electric hybrid vehicle applications, Materials Today: Proceedings, Vol. 13, pp. 688-697, 2019.

[6] Lahyani, A., Sari, A., Lahbib, I., Venet,P.: Optimal hybridization and amortized cost study of battery /supercapacitors system under pulsed loads, Journal of Energy Storage, Vol. 6, pp. 222-231, 2016.

[7] Bououchma, Z. andSabor,J.: Online diagnosis of supercapacitors using extended Kalman filter combined with PID corrector, Int. J. Power Electron. Drive Syst., Vol. 12, No. 3, pp. 1521, 021.

[8] Abdelhedi, R., Lahyani, A.C., Ammari, Sari, A., Venet,P.: Reinforcement learning-based power sharing between batteries and supercapacitors in electric vehicles, in: *2018 IEEE International Conference on Industrial Technology*, 20-22.2.2018, Lyon,pp. 2072-2077.

[9] Abdelhedi, R., Ammari, A.C., Sari, A., Lahyani, A., Venet, P.: Optimal power sharing between bat–teries and supercapacitors in Electric vehicles, in: *2016 7th International Conference on Sciences of Electronics, Technologies of Information and*

Telecommunications, 18-20.12.2016, Hammamet, pp. 97-103.

[10]Liu, Y., Yao, C., Guo, C., Yang, Z., Fu,C.: Energy-Saving Optimization for Electric Vehicles in Car-Following Scenarios Based on Model Predictive Control, World Electr. Veh. J., Vol. 14, No. 2, pp. 42, 2023.

[11] Xu, B., Shi, J., Li, S., Li, H., Wang, Z.: Energy Consumption and Battery Aging Minimization Using a Q-learning Strategy for a Battery/ Ultra–capacitor Electric Vehicle, Energy,Vol. 229,pp. 120705, 2021.

[12] Van den Hurk. J., Salazar, M.: Energy-optimal De–sign and Control of Electric Vehicles' Trans–missions, in: *2021 IEEE Vehicle Power and Propu–l#sion Conference*, 25-28.10.2021,Gijon, pp. 1-7.

[13] Kozłowski, E., Wiśniowski, P., Gis, M., Zima–kowska-Laskowska, M., Borucka, A.: Vehicle Acceleration and Speed as Factors Determining Energy Consumption in Electric Vehicles, Ener–gies, Vol. 17, No. 16, pp. 4051, 2024.

[14] English, L.Q., Mareno, A., Chen, X.L.: Optimizing regenerative braking -- a variational calculus app–roach, Math. Probl. Eng., Vol. 2021, pp. 8002130, 2021.

[15] Gao, Z. et al.: Real-Time Self-Adaptive Reinfor–cement Learning Controller for Energy Manage–ment of Hybrid Electric Tractor Based on Working Condition Identification, 2024, *Elsevier BV*.

[16] Das, R., Wang, Y., Putrus, G., Kotter, R., Marzband, M., Herteleer, B., Warmerdam J.: Multi-objective techno-economic-environmental optimi–sation of electric vehicle for energy services, Applied Energy, Vol. 257, pp. 113965, 2020.

[17]Song, Z. et al.: Multi-objective optimization of a semi-active battery/supercapacitor energy storage system for electric vehicles, Applied Energy, Vol. 135, pp. 212-224, 2014.

[18] Pahlevaninezhad, M., Hamza, D., Jain, P.K.: An Improved Layout Strategy for Common-Mode EMI Suppression Applicable to High-Frequency Planar Transformers in High-Power DC/DC Converters Used for Electric Vehicles, IEEE Trans. Power Electron., Vol. 29, No. 3, pp. 1211-1228, 2014.

[19] Abdelhedi, R.: *Optimization of a hybrid electrical energy storage system with battery and super–capacitors for electric vehicles*, PhD thesis, Natio–nal Institute of Applied Sciences and Technologies, Claude Bernard Lyon 1 University,Lyon, 2018.

[20] Bouyarmane, H., El Amine, M., Sallaou, M.: Early environmental assessment of products using beha–vior models and the impact of their inaccuracy on environmental product performance, FME Trans., Vol. 50, No. 4, pp. 715-723, 2022.

[21] Harrington, E.C.: The Desirability Function,Ind. Qual. Control, Vol. 21, pp. 494-498, 1965.

[22] Derringer, G., Suich, R.: Simultaneous Optimiza–tion of Several Response Variables, J. Qual. Tech–nol., Vol. 12, No. 4, pp. 214-219, 1980.

[23] Scott, M.J., Antonsson, E.K.: Aggregation functi–ons for engineering design trade-offs, Fuzzy Sets Syst.,Vol. 99, No. 3, pp. 253-264, 1998.

[24]Lazaar, N., Fakhri, E., Barakat, M., Gualous, H., Sabor,J., ENSAM, University of Moulay Ismail. Morocco, Optimal sizing of Marine Current Energy Based Hybrid Microgrid, *REPQJ*, vol. 18, p. 515□521, juin 2020.

[25] Lazaar,N.: *Optimization of Data Center Power Supplies*, PhD thesis, Normandy in joint super–vision with Moulay Ismaïl University, Meknes, 2021.

[26] Madani, S.S., Shabeer, Y., Allard, F., Fowler, M., Ziebert, C., Wang, Z., Panchal, S., Chaoui, H., Mekhilef, S., Dou, S.X., See, K., Khalilpour, K.: A Comprehensive Review on Lithium-Ion Battery Lifetime Prediction and Aging Mechanism Analysis, Batteries, Vol. 11, No. 4, pp. 127, 2025.

[27] Menye,J.S., Camara,M.B., Dakyo,B.: Lithium Bat–tery Degradation and Failure Mechanisms: A State-of-the-Art Review, Energies, Vol. 18, No. 2, pp. 342, 2025.

[28] Xiong, R., Wang, P., Jia, Y., Shen, W., Sun,F.: Multi-factor aging in Lithium Iron phosp–hate batteries: Mechanisms and insights,Appl. En–ergy, Vol. 382, pp. 125250, 2025.

[29] Askarzadehardestani ,M., Essmann, S., Schröder, D.: Exploring the Impact of Prior Degradation on the Performance and Lifetime of Second-Life Li-Ion Batteries, Batteries Supercaps, 2025.

[30] Rajkovic, M., Zrnic, N., Kosanic, N., Borovinsek, M., Lerher, T.: A multi-objective optimization model for minimizing cost, travel time and Co2 emission in an AS/RS, FME Trans.,Vol. 45, No. 4, pp. 620-629, 2017.

NOMENCLATURE

E_d	demanded energy
E_{lb}^i	energy of the LBs at time i
E_{sc}^i	energy of the SCs at time i
P_d	demanded power
P_{lb}	maximum power delivered by the LB
p_i	performance indexes
P_{ns}	nominal power of SC
P_{nb}	nominal power of LB
N_{lb}	number of battery cells
N_{sc}	number of super-capacitors
T_d	driving time
w_i	criterion weight
z_i	desirability indexes

Greek symbols

η_{inv}	inverter efficiency
ΔT	Time step

Acronyms

EoL	end-of-life
ESD	energy storage design
EV	electric vehicle
GSI	generalized satisfaction index
LB	lithium batteries
SC	supercapacitor
SoC	state of charge

ОПТИМИЗАЦИЈА ХИБРИДНИХ СИСТЕМА ЗА СКЛАДИШТЕЊЕ ЕНЕРГИЈЕ СА БАТЕРИЈАМА/СУПЕРКОНДЕНЗАТОРИМА У ЕЛЕКТРИЧНИМ ВОЗИЛИМА УСМЕРЕНА НА КОРИСНИКА

П. Бомушма, М. Ел Амине

Овај рад представља вишециљни приступ оптими–зацији за пројектовање хибридних система за скла–диштење енергије који комбинују литијумске батерије и суперкондензаторе у електричним вози–лима. Развијен је оквир заснован на пожељности како би се интегрисали вишеструки конфликтни циљеви, укљу–чујући домет вожње, трошкове система, век трајања и попуњеност запремине. Сваки циљ се трансформише у нормализовани индекс задовољства коришћењем параметризованих функција пожељно–сти изведених из корисничких префе–ренција. Ови индекси се агрегирају у глобалну мет–рику пер–форманси како би се водио процес оптимизације. Генетски алгоритам се користи за идентификацију оптималних конфигурација које балансирају комп–ромисе између циљева. Резултати показују да хиб–ридни систем значајно побољшава домет вожње и век трајања, а истовремено смањује трошкове и запре–мину у поређењу са системима који раде само на батерије. Предложена метода нуди флексибилну и стратегију пројектовања усмерену на корисника за побољшање перформанси и поузданости електричних возила.