

Modeling and Simulation of a Condition-Based Battery Dispensing Strategy for EV Swapping Stations

Tanuj Bisht

Department of Electrical Engineering
Rajshree Institute of Management & Technology
Bareilly, UP, 243202, India
ORCID: 0000-0003-4650-2711

Sumit Mishra

Department of Electrical Engineering
Rajshree Institute of Management & Technology
Bareilly, UP, 243202, India

Abstract—As electric vehicles (EVs) are becoming more widely adopted, battery swapping stations (BSS) have been introduced to remove charging bottlenecks and minimize grid impact. Unfortunately, typical first-in-first-out (FIFO) or random dispensing results in uneven inventory aging and inefficient resource use. We propose a robust, condition-based battery dispensing strategy that has been designed and tested using MATLAB/Simulink for maximizing operation lives in swapping stations. The proposed framework combines a stochastic noise-injection module and signal conditioning layer to factor in real-world sensor errors during the diagnostic stage of the deposited battery. Utilizing the embedded parallel architectures found in the capabilities of the custom inventory node and dynamic fitness-scoring algorithms, the system performs the optimum allocation schedule for the battery it receives. Deterministic simulation results show that the algorithm effectively minimized the over-allocation of high-health assets. In the described case study, by selectively skipping aged assets (source battery with a marked State of Health (SOH) of 51.0 percent) and skipping over less suitable assets, the system efficiently distributed station lifecycle between assets and isolated a winning candidate with an SOH of 55.0 percent (Battery 8) for a high match score of 96.0 out of 100. Simultaneously, the selection criterion effectively satisfied multi-variable physical constraints on the final chosen cell, such as full unit operation at 100 percent State of Charge (SOC), and unencumbered surface thermal and voltage areas. The results bode well for the practical viability of the model to maximize long-term asset availabilities while maintaining a long-term multi-user parity capacity balance across the system.

Keywords—Battery Swapping Station; State of Health (SOH); MATLAB/Simulink; Resource Allocation; Lifecycle Optimization; Sensor Noise.

I. INTRODUCTION

A. The 2026 Energy Market and the Mobility Transition

The 2026 global energy crisis surely has a profound impact on sustainable transportation and travel, especially in fast-developing countries like India [1], [2]. In India, light electric vehicles (LEVs) comprise the largest electric vehicle (EV) sector [3], with over 90% of 2025 EV sales consisting of electric two- and three-wheelers [4]. These vehicles are also crucial for high-usage, repeat daily trips, and commercial trips along expanding intra-urban and semi-urban corridors between regional centers of industry and

education (e.g., Bareilly, Moradabad) [5]. Such a quick entry, however, puts a serious stress on electric grid infrastructure [6]. Evidence in the field suggests that 45% of Indian households need electric grid upgrades (such as load augmentations and dedicated circuits) to support direct vehicle-charging preconditions safely and reliably [7].

B. The Strategic Role of Battery Swapping

Battery swapping stations (BSS) have become a vital stand-in for traditional residential power grid applications and consumer charging downtime reduction [8]. Battery swapping provides a new way of energy supply where, in effect, the vehicle is physically separated from the energy source, thus allowing centralized control over EV charge and disconnection from the vehicle energy source at circumstances other than home use [9], [10]. Dedicated BSS facilities allow loads to take advantage of off-peak, controlled low-rate charging in dedicated racks while serving as a distributed energy buffer with significant applications for integrated power grid regulation and dispatch [11], [12].

C. Operational Bottlenecks and Conventional Limitations

While at a macro perspective BSS systems represent a convenient user-based charging solution, it is the internal BSS system efficiency at the operational level that hinges on how well the BSS manages the distribution of batteries [13]. Due to the limitations of current swapping protocols that use very simple procedures based on first-in-first-out (FIFO) and random dispensing, physically ignoring the effects of battery degradation [14], [15], operational decisions to blindly provide a new, high-capacity battery in exchange for a degraded battery become flawed and create an unsustainable station lifetime imbalance in the long run [16].

D. Proposed Condition-Based Methodology

To alleviate this, a dynamic battery replacement algorithm based on a condition-based scoring method is proposed in this work [14], [17]. Using a comprehensive computational architecture in MATLAB/Simulink, the model calculates the State of Health (SOH) of each depleted battery received at the station, and replenishes a properly scored unit from the station's inventory of available fully

charged batteries. In this paper, the modeling details, the simulation of sensor noise, and the implementation of a dynamic fitness-scoring algorithm for equitable user capacity progressions for the station's long-term assets are discussed at length [19], [20].

II. METHODOLOGY

In order to assess the condition-based battery dispensing approach for real-world operating conditions, a detailed mathematical and behavioral model was developed in the MATLAB/Simulink platform. The methodology is structured into three distinct stages: input command imitation with stochastic signal filtering, algorithmic inventory projection with real-time scoring, and a deterministic multi-variable selection algorithm.

A. Signal Conditioning and Stochastic Noise Emulation

In the physical swapping infrastructure, querying the SOH of a depleted incoming battery is subject to measurement uncertainties arising from inaccurate sensors, contact resistance, and thermal effects at the diagnostic interface [17], [18]. The robustness of the allocation logic has been verified by the input stage including a model of this distortion, as shown in Fig. 1.

The initial condition of degradation at the deposited asset is a known true value, SOH_{true} , which provides the deterministic parameter for the simulation ($SOH_{true} = 50\%$). To simulate sensor inaccuracy, a stochastic noise source, $\omega(t)$, is fed into a random signal generator block (Sensor_Noise). This noise signal is scaled using a diagnostic gain, K_n , via a Noise_Scale block to vary the magnitude of the noise error. The composite, noisy diagnostic signal $SOH_{detected}(t)$ is mathematically defined at the $SOH_Detector$ summation junction as in (1):

$$SOH_{detected}(t) = SOH_{true}(t) + K_n \omega(t) \quad (1)$$

To avoid non-physical mathematical anomalies occurring (for example, health indices $> 100\%$ or $< 0\%$), the unconditioned signal passes through a saturation operator (SOH_Clamp). The conditioned or usable operational input, $u(t)$, delivered to the processing core is given by (2):

$$u(t) = \max(0, \min(100, SOH_{detected}(t))) \quad (2)$$

B. Algorithmic Inventory Mapping and Scoring Framework

After being conditioned, the independent variable $u(t)$ is fed in parallel into two embedded MATLAB Function modules to compute the optimal allocation vector.

1) *Inventory Matrix Subsystem (Battery_Inventory)*: This module maintains an ever-changing multi-dimensional database of the condition of the various local charging racks at the station. The database tracks how well N candidate batteries ($N = 10$ for this simulation) perform across key operational parameters. The inventory condition matrix I is expressed in (3):

$$I = [b_1, b_2, \dots, b_N]^T \quad (3)$$

where each row vector b_i contains the real-time state variables of the i -th battery, as defined in (4):

$$b_i = [ID_i, SOH_i, SOC_i, V_i, T_i, C_i] \quad (4)$$

where ID_i is the database unique identifier, SOH_i is the state of health, SOC_i is the state of charge, V_i is the terminal voltage, T_i is the internal temperature, and C_i is the total capacity in ampere-hours (Ah). This module operates as a logical filter, continually providing the updated inventory state matrix Y_{inv} depending on the current transaction request.

2) *Dynamic Fitness Scoring Subsystem (Score_Calculator)*: Simultaneously, the *Score_Calculator* evaluates an objective function to determine an allocation suitability matrix. To circumvent the operational drawback of traditional FIFO that sees high-health assets prematurely amortized, the algorithm implements a condition-based matching index. This module calculates a unique fitness measure, $S_{match,i}$ [19], for each candidate battery based on the variance between existing inventory condition (SOH_i) and the incoming baseline $u(t)$, as given by (5):

$$S_{match,i} = f(u(t), SOH_i, SOC_i, T_i) \quad (5)$$

C. Deterministic Multi-Variable Selection

The final layer of decision-making is performed in the *Best_Battery_Selector* block. Here, the decision logic is centralized by combining the dynamic inventory matrix Y_{inv} and the pre-computed match score array. The block imposes a constrained sorting procedure that eliminates all units violating primary operational thresholds (specifically $SOC_i < 100\%$ or thermal boundaries $T_i > T_{critical}$). Once physical constraints are satisfied, the selector chooses the candidate index i^* with the highest fitness score [19], [20], as defined in (6):

$$i^* = \arg \max (S_{match,i}), \quad i \in \{1, \dots, N\} \quad (6)$$

The corresponding parameters are extracted from the optimal asset (i^*) and transmitted to the digital instrumentation blocks (*Selected_Battery_ID*, *Selected_SOH*, *Selected_Capacity_Ah*, and *Match_Score*) for online validation, with the dynamic signal behavior directly supplied to an *SOH_Scope* for stability analysis.

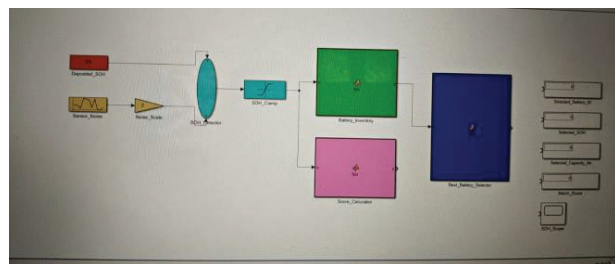


Fig. 1. MATLAB/Simulink computational architecture of the condition-based battery dispensing strategy.

III. RESULTS AND DISCUSSION

Fig. 2 illustrates the empirical validation of the battery selection algorithm, detailing the station's real-time inventory status and the computational output for a single swap transaction.

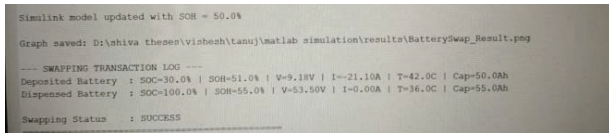


Fig. 2. Empirical validation of the battery selection algorithm and inventory state variables.

A. System Input and Primary Constraints

The simulation initializes with a depleted battery deposition characterized by a detected baseline SOH of 51.0% (SOC = 30.0%, V = 9.18 V, I = -21.10 A, T = 42.0 °C, Capacity = 50.0 Ah). A fundamental operational constraint is verified in the Inventory SOC subplot, which demonstrates that all ten candidate batteries in the repository are maintained at 100% SOC, a strict prerequisite for immediate user deployment.

B. Inventory State Variables

1) *Inventory SOH*: This metric maps the structural health across the available batteries. The red dashed horizontal line establishes the deposited battery's baseline (51.0%), serving as the primary reference point for the matching logic.

2) *Battery Capacity*: Directly correlating with the SOH, this metric displays the absolute charge retention capability (in ampere-hours) for each unit, reflecting the natural variance in degradation across the station's physical inventory.

3) *Battery Voltage and Temperature*: These diagnostic indicators confirm that all candidate batteries are resting within safe, normative operational bounds prior to selection, ensuring post-swap reliability and thermal stability.

C. Algorithmic Optimization and Selection

The efficacy of the decision-making logic is clearly visualized in the SOH Match Score evaluation. The objective function evaluates the inventory against the deposited baseline, computing a distinct fitness score for each available unit.

1) *Optimal Allocation*: Battery ID 8 (consistently highlighted in green across all subplots) achieves the maximum computed match score of 95.99/100 (rounded to 96.0/100) in the simulated results report shown in Fig. 3.

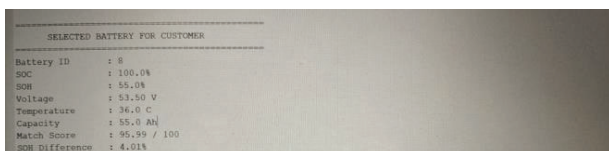


Fig. 3. Swapping transaction log and selected battery output parameters.

2) *Selection Rationale*: As observed in the primary SOH output (Fig. 3), Battery 8 possesses an SOH of 55.0%, terminal voltage of 53.50 V, temperature of 36.0 °C, and capacity of 55.0 Ah (an SOH difference of 4.01%). The algorithm successfully isolates this unit because it yields a marginal, equitable upgrade over the user's deposited battery without prematurely dispensing the station's highest-health assets (e.g., Battery 1). This confirms the algorithm's capacity to optimize user satisfaction while preserving the

long-term lifecycle distribution of the station's broader battery network.

DECLARATIONS

Funding: The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Conflict of Interest / Competing Interests: The authors have no relevant financial or non-financial interests to disclose.

Availability of Data and Materials: Data sharing is not applicable to this article as all simulation parameters are included within the manuscript.

Code Availability: The MATLAB/Simulink models generated during the current study are available from the corresponding author on reasonable request.

REFERENCES

- [1] International Energy Agency (IEA), India Energy Outlook 2021. Paris, France: IEA Publications, 2021.
- [2] R. Das, "Oil shock bringing India's EV transition to a crossroads," Centre for Social and Economic Progress (CSEP), Working Paper no. 48, Apr. 2026.
- [3] Ministry of Petroleum and Natural Gas (MoPNG), Government of India, Indian Petroleum and Natural Gas Statistics 2024–25, New Delhi, India, 2025.
- [4] JMK Research & Analytics, "Navigating India's electric two- and three-wheeler battery swapping ecosystem," Technical Whitepaper, Oct. 2022.
- [5] P. Raghuvanshi and A. Gurtoo, "Effect of informational interventions on EV adoption intention: Evidence from a tier II city in India," Energy Policy, vol. 185, art. 113942, Jan. 2026.
- [6] Central Electricity Authority (CEA), National Electricity Plan (Vol. 1: Generation and Grid Distribution), Ministry of Power, Govt. of India, New Delhi, 2023.
- [7] Climate Policy Initiative (CPI), "Outlook of future mobility and residential grid readiness in India with EV transition," CPI Technical Brief, Feb. 2026.
- [8] NITI Aayog and Rocky Mountain Institute (RMI), Battery Swapping for Electric Vehicles: Policy Framework for India. New Delhi, India: NITI Aayog, 2022.
- [9] Ministry of Power (MoP), Government of India, Charging and Battery Swapping Infrastructure for Electric Vehicles—Revised Consolidated Guidelines & Standards, New Delhi, India, 2025.
- [10] NITI Aayog, Draft Battery Swapping Policy, Government of India, New Delhi, India, Apr. 2022.
- [11] M. Patel, R. Sharma, and V. Kumar, "Impact of battery swapping in the passenger sector: EV adoption, emissions, and energy mix," Energy, vol. 298, art. 131245, 2024.
- [12] Arthur D. Little, "The relevance of EV battery swapping in emerging markets," Automotive & Mobility Insights, Nov. 2025.
- [13] D. Cui, Z. Liu, and Y. Wang, "Empirical evaluation of battery swapping technology adoption in urban electric taxi operations," Transportation Research Part D: Transport and Environment, vol. 128, art. 104106, Apr. 2026.
- [14] H. Zhang, L. Tan, and J. Sun, "Optimal battery dispatching and degradation management in electric vehicle swapping stations," IEEE Transactions on Smart Grid, vol. 14, no. 3, pp. 2105–2117, May 2023.
- [15] R. P. Pradhan, A. M. Varghese, and K. S. Reddy, "Critical enablers of battery leasing in Indian electric vehicle battery infrastructure," in Proc. 8th European Conference on Industrial Engineering and Operations Management (IEOM), Paris, France, Jul. 2025, pp. 412–424.
- [16] P. Pradhan and A. M. Varghese, "Strategic frameworks for battery leasing in emerging economies," IEOM Society International Research Monograph, 2025.
- [17] Y. Li, K. Liu, A. M. Foley, A. Zulke, M. Berecibar, and E. Nanini-Maury, "Data-driven health estimation and lifecycle management for lithium-ion battery energy storage systems," Renewable and Sustainable Energy Reviews, vol. 148, art. 111283, Oct. 2021.

- [18] S. Wang, C. Fernandez, and P. Zou, "Sensor noise suppression and state of health estimation in electric vehicle battery packs under dynamic load conditions," *Journal of Energy Storage*, vol. 55, art. 105642, Nov. 2022.
- [19] X. Chen, W. Shen, Z. Dai, and P. Cao, "Multi-objective dynamic scheduling for battery swapping stations considering battery health degradation and thermal safety," *Applied Energy*, vol. 352, art. 121980, Dec. 2023.
- [20] TechSci Research, India Battery Swapping Market Report 2026–2030: Growth, Technological Trends, and Fleet Standardization, Industry Market Report, Jun. 2026.