The Road to Zero-Emission Fleets: The Role of Data-Driven Decision-Making

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Aivars Rubenis
Latvia University of Life Sciences and Technologies

Jelena Tonova
ISMA University of Applied Sciences

Vadims Morozovs
Vozorom, SIA

Contact information:
Phone: +371 29 462 363
aivars.rubenis@lbtu.lv

The application of multi-objective optimization provides a principled method for exploring trade-offs between total cost of ownership and greenhouse gas emissions, thereby aligning fleet transition strategies with both economic constraints and sustainability goals.

Despite benefiting from tax exemptions, corporate cars lag in reducing Europe's transport emissions. In the EU, corporate vehicles account for 60% of new car registrations and, as they drive twice as much as private vehicles, they contribute 74% of new car CO_2 emissions

While financial considerations play a central role in fleet replacement decisions, businesses must also assess a broader range of factors beyond cost alone. A key question is whether the new vehicle technology—particularly battery electric vehicles (BEVs)—can reliably support the operational demands of the company.

A structured, data-driven framework for fleet transition enables organizations to systematically optimize both financial and environmental outcomes for evidence-based decision-making.

The accuracy and reliability of fleet modelling depend on robust data preprocessing techniques, which harmonize units, interpolate missing values, and eliminate anomalous entries across heterogeneous data sources.

Scenario-based simulation enhances strategic planning.

Introduction

In this paper, we propose a framework for a data-driven decision-support system that integrates fleet monitoring based on carmonitor.eu database. scenario simulations, and tailored recommendations.

The paper outlines key framework parameters and the next steps toward developing a robust, scalable tool for fleet transition optimization. Through this approach, businesses can make informed, strategic decisions that accelerate their path toward zero-emission mobility while ensuring economic and operational feasibility.

Methodology

A conceptual foundation is the total cost of ownership (TCO)

$$TCO_i = I_i + \sum_{t=o}^{T_i} \frac{M_{i,t} + E_{i,t}}{(1+r)^t} - \frac{R_{i,T_i}}{(1+r)^{T_i}},$$

Enhancing TCO with Functional & Behavioural Metrics:
In addition to economic factors, the research examines charging infrastructure and energy demand considerations, recognizing these as critical barriers to fleet electrification.

Building modelling functions for system optimisation.

Result: Mathematical Model

Traditional TCO
- Investments (fleet availability, costs, financing, remaining value), Gov't incentives
- Fleet operational data (trip distances, refueling patterns, vehicle usage times)
- Charging infrastruc-ture availability and grid dependency

Operational impact
- Assessing how charging time constraints affect fleet deployment and route modifications.
- Evaluating charging station accessibility in business districts

Driving Habits
- Driver behavior data (acceleration, braking, idle time)
- Comparing ICE vs. EV energy consumption under different driving styles.

Pychological Adaptation
- Measuring employee resistance or willingness to adopt nighttime charging routines.
- Behavioral modeling of transition barriers.

Set of parameters:

$$\boldsymbol{v_i} = \left(\text{type}_i, P_i, \delta_i, e_i, c_{\text{fixed},i}, \text{soc}_i(t), \text{range}_i, \text{fuel}_i, \text{tech}_i\right)$$

Preprocessing function *Π* integrates and harmonizes data sources:

$$S = \Pi\left(D_{\text{tele}}, D_{\text{ops}}, D_{\text{ext}}\right)$$

- Standardizing Data Formats and Units
- Handling Missing Data
- Detecting and Correcting Anomalies
  - Treshold filtering $|f_{i,t+\Delta t} - f_{i,t}| > \varepsilon_{\mathrm{i}}$
  - GPS Error filtering $\frac{\left\| r_{i,t+\Delta t} - r_{i,t} \right\|}{\Delta t} > v_{max_{r_{i,t}}}$
- Aggregation & Harmonization Across Sources

$$\overline{f_{i,t}} = \frac{1}{N} \sum_{j=1}^{N} f_{i,t-j}$$

Cost Function C(σk) evaluates the monetary outlay (in total cost of ownership terms) for each vehicle or scenario configuration.

$$C(\sigma_k) = P_i + \sum_{t=1}^{T}\left(m_{i,t} + c_{fixed,i}\right) + \sum_{t=1}^{T}\left(f_{i,t} \times p_{fuel\ or\ elec,t}\right) - Res(i_T)$$

emissions function $E(\sigma_k)$ calculates the greenhouse gas output.

$$E\left(\sigma k\right) = \sum_{t=1}^{T}\left(d_{i,t} \times e_{\text{ICE or EV}}\right),$$

An optimization routine is then invoked separately for each scenario, producing a scenario-specific optimal solution:

$$\boldsymbol{X}_k^* = \min_{X}\left[\alpha \cdot C\left(\boldsymbol{X}, \Theta_k\right) + \beta \cdot E\left(\boldsymbol{X}, \Theta_k\right)\right],$$

scenario k can be represented as a vector of assumptions:

$$\Theta_k = \left(p_{\text{fuel}}, p_{\text{elec}}, e_{\text{ICE}}, e_{\text{EV}}, \phi_{\text{policy}}, \dots\right)_k$$

scenario's feed into the simulation-optimization stage of the framework:

$$Y_k = Sim\left(S, \Theta_k, \boldsymbol{X}\right),$$

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