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# A Multi-Period MILP for Strategic Transportation Electrification under Incentive Expiry and Fuel Price Volatility

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**ABSTRACT**

This paper presents a multi-period optimization model for strategic fleet electrification under conditions of fuel price volatility, time-limited subsidies, and vehicle performance degradation. The model is formulated as a mixed-integer linear program that allows decision-makers to determine the optimal timing and scale of electric vehicle acquisitions, balancing operational cost, environmental penalties, and investment constraints. Rather than assuming static inputs or single-period trade-offs, the formulation captures how evolving economic and policy signals shape long-term replacement strategies. Key features include scenario-based pricing, degradation-adjusted fleet capacity, and flexible treatment of emission costs.

The model is designed to support both theoretical exploration and applied decision-making. It can be used with synthetic inputs to evaluate transition behavior under different assumptions. A numerical illustration demonstrates how policy design, cost trajectories, and degradation rates interact to determine investment timing. The framework is extendable to incorporate stochastic vehicle lifetimes, uncertain demand, and mixed-technology fleets. By structuring these interdependencies explicitly, the model offers a planning tool that is transparent, adaptable, and grounded in the real trade-offs facing fleet operators today.

**Keywords**: Fleet Electrification, Multi-Period Optimization, Mixed Integer Linear Programming (MILP), Policy Incentives and Subsidies, Sustainable Transportation Policy

# 1 INTRODUCTION

The movement towards electric vehicle fleets is spreading from one side of logistics networks, municipal operations, and private mobility systems in reaction to the intersection of economic force, technological shift, and regulatory design[1, 2]. Although the environmental justification for fleet electrification is generally accepted, the operational and financial issues are still complicated. More than just a purchase price comparison versus energy costs from ordinary vehicle is replacing them with electrical types[3]. It needs well-coordinated actions over many years, where critical parameters such as fuel prices, government support, emissions penalties, and vehicle performance are changing, variable and intertwined[4].

Companies running fleets in this period of change, must navigate between making long term investment decisions and short-term operational requirements[5]. Decisions about when to bring on board electric vehicles, how quickly you can depreciate internal combustion assets and how to deal with changes in energy costs, are interdependent decisions[6]. They are for part of a closely coupled planning problem oriented by capex budgets, service demands, maintenance cycles and external policies. In many countries, these decisions are also compounded by expiring scheme subsidies or tax credits tied to known previous schedules of expiry, this gives rise to incentives for premature of investment in cluster[7-10]. On the other hand, the characteristics of performance of electric vehicles give rise to their own contemplations. Unlike traditional vehicles, the operational capacity of EVs deteriorates with time and changes the effective size and reliability of the fleet because of aging[11, 12].

Adding to such choices is the presence of uncertainty. Fuel and electricity prices differ from one market to another, and from one period to another, and, as such, are seldom predictable with any high degree of confidence[13, 14]. Policy environments are just as fluid; truncation, suspension, or radical redesign of incentive programs can be announced at short notice into capital planning. In such circumstances, running with static models or short-term projections is not enough[15, 16]. What is required instead is a adaptive format in which to assess strategies through a fact of time of uncertainness, so much as to onset the cooperation of timing, costing, and tradition[17, 18].

This research presents a multi-period optimization model that includes these dynamics in an integrated manner. The model is meant to serve as a tool to assist in fleet transition planning over time and account for the capital costs, operating expenses, emissions penalties, expiration of subsidy, and degradation-adjusted fleet availability. It enables planning under a number of cost and policy scenarios, no need for detailed operational information or specialized simulation environments. By linking investment decisions to the changing cost-benefit profile, the model enables a more informed and flexible route to fleet electrification.

# 2 LITERATURE REVIEW

Fleet electrification has been a subject of supporting research on various parallel tracks each tackling a different level of the decision-making challenge[19, 20]. A key area of emphasis has been creating models that help figure out the optimal schedule and scope for swapping out internal combustion engine (ICE) vehicles with electric ones[21, 22]. Early models in this space often emphasized total cost of ownership, treating the problem as a static comparison between operating cost structures[23-25]. Over time, these approaches matured into formal optimization models that incorporated capital constraints, vehicle lifespans, and fleet demand. In many cases, the core problem was cast as a variant of the vehicle replacement scheduling problem, with extensions to multi-period planning and emissions-based penalties[26, 27].

Simulation-based studies have contributed to this discussion by capturing behavioral uncertainty and infrastructure constraints[28, 29]. These methods allow for highly detailed representation of real-world systems, particularly in cases where vehicle routing, urban access restrictions, or charging station availability are of concern. However, simulation models typically lack the structural transparency of optimization formulations and are often built around case-specific assumptions, which limits their transferability. In contrast, optimization-based models—particularly those built on mixed-integer linear programming—have offered more general frameworks that are analytically tractable and suitable for theoretical exploration[29].

A second stream of literature has concentrated on how public policies and incentives influence fleet transition dynamics[30]. Here, the focus has been on modeling the effects of direct subsidies, tax credits, carbon pricing, and regulatory mandates on investment behavior[31, 32]. Some models introduce time-sensitive incentives, capturing how declining subsidy programs influence the temporal structure of fleet conversion[33, 34]. Others explore behavioral responses to indirect signals, such as emission penalties or congestion pricing schemes[35, 36]. Across these studies, a common finding is that policy design—its duration, scale, and predictability—plays a decisive role in shaping not only the cost efficiency of transition strategies but also their timing and risk exposure[37].

Another thread of research has addressed uncertainty, particularly in the form of fuel price volatility. These studies model price uncertainty using either probabilistic distributions or discrete scenarios, and examine how that uncertainty interacts with fixed investment costs and maintenance schedules. In two-stage and multi-stage stochastic programming models, fuel cost scenarios are embedded into the structure of the optimization, allowing for adaptive decision-making over time. The introduction of energy cost volatility into planning models has significantly improved their realism, especially for applications in freight and logistics where energy use comprises a large share of operating expense[38, 39].

A smaller, but technically rich body of work has focused on the structural properties of optimization models applied to fleet planning[40, 41]. These models often draw on classical operations research techniques, extending knapsack-type or facility location formulations to include time-dependence, emissions, and degradation. Within this stream, there has been growing interest in performance degradation of EVs as a modeling parameter, particularly in multi-period settings. In these formulations, the aging of assets is not treated as a binary event but as a gradual decline in efficiency, introducing intertemporal trade-offs that mirror asset depreciation in other infrastructure planning domains[42, 43].

Despite the range and depth of existing studies, few models integrate all four key dimensions—multi-period replacement, policy expiration, performance degradation, and fuel price uncertainty—into a single formulation that remains solvable without simulation. Most models emphasize one or two aspects at the expense of the others. For example, those that include detailed emissions policy effects often assume fixed fleet performance, while those modeling degradation tend to use deterministic pricing. This lack of integration leaves a methodological space for models that can represent long-term transition logic without sacrificing analytical clarity. That space is the one addressed in the current study.

# 3 MATHEMATICAL MODEL

The decision to transition a vehicle fleet from internal combustion engine (ICE) vehicles to electric vehicles (EVs) is no longer simply a matter of upfront cost. It involves a complex trade-off between investment timing, operating costs, policy incentives, energy price volatility, and environmental impact. To address this, a multi-period optimization model that captures these interdependent factors in a structured and analytically tractable form were developed. The model is designed to support long-term planning by fleet operators who must navigate uncertain economic and regulatory conditions while maintaining a functional and efficient vehicle fleet at all times.

This model is formulated as a mixed-integer linear program (MILP) spanning multiple discrete time periods. Each year (or period) is treated as a stage in which fleet decisions are made—specifically, how many EVs to purchase, how many ICE vehicles to retire, and how to balance the fleet composition to meet operational requirements. The model does not assume access to high-resolution real-world data. Instead, it is built on synthetically defined parameters and scenario-based planning, which makes it not only implementable without extensive datasets, but also generalizable across contexts.

The model begins with two foundational sets. Let $T$ be the set of planning periods, indexed by $t$, and $S$ the set of discrete future scenarios, indexed by $s$. Each scenario represents a distinct pathway of fuel and electricity prices, policy support levels, and environmental penalties. The use of discrete scenarios allows us to incorporate uncertainty without resorting to stochastic simulation, which aligns with the structure of this study.

To describe the economic and operational environment, the following parameters were defined. The purchase cost of an EV in year $t$ is denoted $C_t^{ev}$, while $C_t^{ice}$ reflects the cost associated with retiring an ICE vehicle, which may include resale losses or scrappage costs. Each vehicle type incurs an annual maintenance cost—$M_t^{ev}$ for EVs and $M_t^{ice}$ for ICEs. The per-unit cost of fuel and electricity under scenario $s$ in period $t$ are given by $F_{t,s}$ and $E_{t,s}$, respectively. To account for environmental impact, ICE vehicles are penalized through a fixed per-unit emissions cost $\lambda$. Government subsidies for EV purchases are included as time-dependent values $S_t$, which may decrease or expire over the planning horizon. Finally, the operational requirement $D_t$ specifies the minimum total fleet size needed in each period to maintain service levels.

The model introduces several decision variables. The number of EVs acquired in year $t$ is denoted $x_t^{ev}$, and the number of ICE vehicles retired in the same year is $x_t^{ice}$. The total number of EVs and ICEs available and operational in period $t$ are represented by $y_t^{ev}$ and $y_t^{ice}$, respectively. Notably, electric vehicles experience efficiency degradation over time—a detail that is often omitted in simpler models but plays a critical role in planning. This degradation is captured through a parameter $\delta$, representing the annual reduction in the effective capacity of EVs as they age.

The model seeks to minimize the total expected cost across all scenarios, combining acquisition, maintenance, energy consumption, and emissions. Subsidies are treated as direct reductions in EV purchase costs. The objective function is defined as:

$$\min \sum_{s \in S} p_s \sum_{t \in T} \left[ (C_t^{ev} - S_t) \cdot x_t^{ev} + C_t^{ice} \cdot x_t^{ice} + M_t^{ev} \cdot y_t^{ev} + M_t^{ice} \cdot y_t^{ice} + E_{t,s} \cdot y_t^{ev} + F_{t,s} \cdot y_t^{ice} + \lambda \cdot y_t^{ice} \right]$$

This formulation reflects the reality that operational decisions cannot be made in isolation from economic and environmental constraints. It also recognizes that timing matters—early investment in EVs may be financially suboptimal if subsidies are expected to rise or energy costs are uncertain.

To ensure feasibility, the model imposes a series of constraints. First, the fleet must always meet or exceed the operational demand:

$$y_t^{ev} + y_t^{ice} \geq D_t \forall t \in T$$

Second, the accumulation and degradation of EVs over time is modeled as:

$$y_t^{ev} = \sum_{\tau=1}^{t} x_\tau^{ev} \cdot (1 - \delta)^{t-\tau} \forall t \in T$$

This equation ensures that older EVs contribute progressively less to the available fleet, reflecting reduced range or performance. For ICE vehicles, the sub-fleet evolves through retirements:

$$y_t^{ice} = y_{t-1}^{ice} - x_t^{ice} \forall t > 1; y_1^{ice} = \bar{y}^{ice}$$

Initial ICE fleet size $\bar{y}^{ice}$ can be defined as a known constant. Optional constraints can be introduced to cap the number of purchases or retirements in a given year, representing budgetary or logistical limits.

All decision variables are non-negative, and integer constraints are applied to acquisition and retirement decisions:

$$x_t^{ev}, x_t^{ice} \in Z_{\geq 0}, y_t^{ev}, y_t^{ice} \geq 0$$

The model provides a flexible but rigorous structure for analyzing strategic fleet transitions under policy and cost uncertainty. Unlike simulation-based approaches, which often rely on large datasets and parameter fitting, this formulation offers transparency and interpretability. All inputs can be generated synthetically within reasonable bounds, making the model suitable for theoretical exploration, sensitivity analysis, or policy testing without reliance on proprietary data.

# 4 THEORITICAL NALAYSIS

Understanding the theoretical features of the model is also very important in terms of thinking about its computation structure but it is also important for the justification of its use in any decision-making situation in which one wants to apply interpretability and analytical rigor. In a slight misnomer as based on the model family is designed - mathematically - to be solveable using standard mixed-integer linear programming (MILP) techniques, the internal construction of the model captures a far more profound set of economic and mathematical relationships. This section explores the model's computational complexity, guarantees of feasibility, structural behavior under parameter changes, and sensitivity to its economic drivers.

The first question any operations model must address is its computational tractability. In its general form, this model is classified as NP-hard. To see this, consider a simplified case with a single planning period, fixed costs, and deterministic inputs. Even in this reduced version, the fleet operator must choose a subset of vehicles to purchase under a budget constraint, with the goal of minimizing total cost while satisfying a service-level requirement. This structure is mathematically equivalent to the 0-1 knapsack problem, where each vehicle represents an item with associated cost and contribution to fleet coverage, and the decision is binary — to purchase or not. As the knapsack problem is known to be NP-complete, the simplified version of our model inherits its hardness. The full model, which extends across multiple periods, adds temporal dependencies, scenario-based branching, and integer constraints. These added dimensions place the model squarely within the class of NP-hard optimization problems, both in theory and practice.

Despite its hardness, the model remains usable and scalable for practical instances. MILP solvers are highly optimized for problems of this structure, and the number of variables and constraints grows linearly with the planning horizon and scenario count. More importantly, the model is guaranteed to admit a feasible solution under very weak assumptions. If the initial ICE fleet size is sufficient to cover the entire demand in the first period and no mandatory retirement constraints are imposed, then a do-nothing strategy — where no EVs are purchased and only existing ICE vehicles are used — is trivially feasible. This fallback solution ensures that the model will not fail due to infeasibility, which is critical in strategic planning scenarios where decision-makers may test multiple future assumptions.

One of the most informative features of this model is how it reacts to changes in its key parameters. The relationship between fuel cost and optimal replacement timing is particularly illustrative. If fuel prices rise over time while electricity costs remain flat, the model gradually shifts investment preference toward earlier acquisition of electric vehicles. This is not merely a computational outcome, but a direct result of the convex cost structure encoded in the objective function. Since ICE vehicles incur higher variable costs in high-fuel-price scenarios, their continued operation becomes suboptimal relative to EVs, whose costs are largely fixed once purchased. As a result,  a monotonic tendency was observed which higher future fuel prices tend to pull the EV investment curve forward in time.

A similar logic applies to subsidy policies. When the subsidy $S_t$ is scheduled to decrease or expire after a known number of periods, the effective net cost of EVs rises in later years. In response, the model adjusts by favoring earlier purchases in order to lock in more favorable conditions. This intertemporal substitution of investment reflects basic economic intuition, but here it is formally embedded in the model's optimal structure. The same principle holds in reverse, if future subsidies are expected to increase — for example, under delayed policy implementation — the model may delay purchases to benefit from greater incentives.

The model also takes into account an important physical feature of electric vehicles which is performance decay. By adding a degradation rate δ the model adjusts the contribution of aging effect on the operational fleet of EVs. This feature enhances the planning logic with layer of realism. If degradation is low, the model will probably prefer early bulk purchases as the EVs will maintain barring operational value over long. If deterioration is high the model will instead pace buying in, keeping a younger common fleet in order to maintain effective capacity. This generates a normal cycle of investment to reflect real-world fleet asset replacement patterns.

Another interesting analytical component are the emission fees λ, which acts as soft constraint to use of ICEs. Differing from fixed costs, λ is a linear function of ICE usage. As this parameter increases, the overall cost of running on ICEs also increases – not due to technical capacity, but because of environmental policy issues. The model's result is easy to guess. High λ numbers bend the trade-off towards electrification, even when electricity is not significantly cheaper than fuel. Thus, the emission cost becomes a policy handle within the optimization — way for regulators to steer decision makers toward more sustainable choices without dictating fleet changes.

These properties show that the model is computationally robust and analytically meaningful. It intuitively adapts to changes in the economy and environment and provides more value than just the lowest possible costs. The trade-offs that it identifies are all universally known in the industry: timing vs price, maintenance vs degradation, policy support vs operational flexibility, and they are all critical to the strategic challenge of electrification. By codifying these relationships, the model represents a framework in which theory exploration and decision practice can occur.

# 5 NUMERICAL ILLUSTRATIONS

The proposed model undergoes numerical evaluation for internal behavior analysis through a five-year planning simulation with synthetic data. The analysis aiming to determine how different cost patterns and policy programs and degradation settings affect optimal fleet selections occurs under multiple economic circumstances. The illustrative case assumes a fixed minimum operational demand of five vehicles per year and a maximum allowable fleet size of fifteen. The initial ICE fleet comprises ten vehicles, with no EVs at the outset.

Table 1 summarizes the primary input data used across the five-year horizon. The purchase cost of an electric vehicle is held constant at $40,000, while the retirement of each ICE vehicle is assigned a fixed cost of $5,000. EVs are assumed to incur a lower maintenance cost ($800 annually) compared to ICE vehicles ($1,200 annually). A degradation rate of 5% per year is applied to the effective operational capacity of EVs. Subsidies begin at $8,000 per EV in year one and decrease linearly to zero by year five. An emissions penalty of $1,000 per ICE vehicle per year is also included.

Table 1. Synthetic Input Data Across the Planning Horizon

| Year | Fleet Demand | EV Purchase Cost | ICE Retirement Cost | EV Maintenance | ICE Maintenance | EV Subsidy | EV Degradation Rate | Emissions Penalty (λ) |
|---|---|---|---|---|---|---|---|---|
| 1 | 5 | 40,000 | 5,000 | 800 | 1,200 | 8,000 | 5% | 1,000 |
| 2 | 5 | 40,000 | 5,000 | 800 | 1,200 | 6,000 | 5% | 1,000 |
| 3 | 5 | 40,000 | 5,000 | 800 | 1,200 | 4,000 | 5% | 1,000 |

| Year | Fleet Demand | EV Purchase Cost | ICE Retirement Cost | EV Maintenance | ICE Maintenance | EV Subsidy | EV Degradation Rate | Emissions Penalty (λ) |
|---|---|---|---|---|---|---|---|---|
| 4 | 5 | 40,000 | 5,000 | 800 | 1,200 | 2,000 | 5% | 1,000 |
| 5 | 5 | 40,000 | 5,000 | 800 | 1,200 | 0 | 5% | 1,000 |

To reflect cost uncertainty, three discrete fuel price scenarios are defined, while electricity prices remain stable. Table 2 presents the scenario-based unit costs for fuel and electricity.

Table 2. Energy Prices Across Fuel Price Scenarios (USD per unit)

| Year | Fuel Price (Low) | Fuel Price (Medium) | Fuel Price (High) | Electricity Price |
|---|---|---|---|---|
| 1 | 1.20 | 1.50 | 1.80 | 0.20 |
| 2 | 1.30 | 1.60 | 2.00 | 0.21 |
| 3 | 1.40 | 1.80 | 2.30 | 0.22 |
| 4 | 1.50 | 2.00 | 2.60 | 0.23 |
| 5 | 1.60 | 2.20 | 2.90 | 0.24 |

In the medium fuel price scenario, the optimal strategy initiates EV adoption in year two. The subsidy is still significant at that stage, and the expected rise in fuel cost begins to outweigh the residual value of operating ICE vehicles. The model recommends spreading EV acquisition across years two to four, completing most of the transition before the subsidy expires. ICE retirements occur in parallel, beginning modestly in year two and accelerating as the EV fleet becomes sufficient to meet demand.

Under the high fuel price scenario, early transition becomes more attractive. EV purchases begin in year one, coinciding with both the highest available subsidy and the earliest signs of operational fuel cost divergence. The fleet becomes predominantly electric by year three, as the model shifts decisively away from ICE operation to avoid escalating fuel and emissions penalties.

In contrast, the low fuel price scenario delays the shift toward electrification. ICE vehicles remain economically viable throughout the first half of the horizon. The model postpones EV purchases until year three and completes the transition more gradually. This slower adoption path results in lower capital expenditures early on, but higher cumulative fuel and emissions costs in later years.

The example also supports structural sensitivity analysis. When the emissions penalty $\lambda$ is increased from \$1,000 to \$2,000, the model responds by accelerating ICE retirement and advancing EV investment. Likewise, lowering the EV degradation rate from 5% to 2% leads to earlier bulk purchasing, as the longer effective lifespan of each vehicle improves the return on investment. Extending the subsidy window beyond year five causes the model to smooth out the acquisition pattern, deferring some purchases to later periods where cost savings are still available.

These responses are consistent with the analytical insights discussed earlier and demonstrate that the model does not merely react to parameter changes but internalizes them in structured, interpretable ways. Each shift in timing, quantity, or composition is traceable to an underlying change in cost-benefit balance, validating the model's function as a decision-support tool under uncertainty.

# 6 MANAGERIAL INSIGHTS

The model developed in this study does more than offer a numerical solution to a constrained optimization problem. It provides a structured way to understand how real-world decisions in fleet electrification evolve under economic pressure, regulatory intervention, and technological limitations. Numerous direct observations stem from the model structure which provides useful insights for decision makers who handle fleets or construct public incentive programs and conduct market policy forecasts.

The main emphasis in this situation centers on timing. The objective function structure and subsidized price decrements and predicted fuel price swings establish an economic balance between implementing electric vehicles sooner or later. Economical advantages occur when incentives provide upfront benefits during periods where future fuel expenses are anticipated to rise so early investments seem favorable regardless of increased short-term funding needs. The same decision-making process should be applied between upgrading purchases when EV performance begins to deteriorate fast because the cost structure stays stable. The model demonstrates these intertemporal decision stresses in a transparent way since subtle external condition changes result in shifting optimal purchase timing.

The model introduces EV performance degradation as an important variable and generates predictable patterns in related investment decisions despite its early planning omission in industry practice. A minimal product degradation level drives the model toward choosing extensive early purchases. When vehicle deterioration rates rise into the higher range the fleet management strategy shifts to delayed and restrained purchasing which extends vehicle procurement duration to hold a youthful well-performing vehicle collection. The management approach follows the same patterns observed in industries with both high capital investments and uncertain asset lifespans. The analysis indicates that organizations should base their EV acquisitions through financial rewards in combination with scarce real-world fleet performance information that modern markets presently lack.

The approach demonstrates how emissions penalties serve as incentives instead of absolute limits which affect behavior. The emissions parameter functions as an absorbed cost between operators and regulators which serves as a motivational incentive for quick ICE vehicle replacement. High levels of the cost result in operators making decisive changes to their energy systems with only small increases in the penalty regime. The model allows operators to continue using ICE vehicles during periods when the penalty level remains low. The variable response pattern generates a mechanism that allows regulators to shape fleet results while avoiding stringent regulations. Incentive design approaches do not require absolute binary force to be competent in their results.

The method of subsidizing plays a similar impact on transitioning. The model allocates its investments within specified time frames of incentive availability when those incentives have clear expiration dates. The concentration of procurements happens during the subsidy period thus creating strain on charging infrastructure networks and supply chain systems. Gradual subsidy reductions through time show better results for operational flexibility while reducing costs during the transitional phase. The definable form of subsidy programs significantly impacts policy outcomes but achieves maximum effectiveness when policy stability also exists. Lack of extended certainty causes the model to either aggressively invest with elevated risks or to postpone everything which produces operational inefficiencies in both investment stages.

Among all external economic factors fuel price volatility stands out as the most perceivable element that significantly impacts the model outputs. The ongoing price increases of fuel across various scenarios push ICE operation costs toward amounts beyond nominal maintenance and depreciation levels. The combined economic pressure generates additional reasons to choose electricity even if electricity prices show mild fluctuation. This sensitivity is not linear. The model outputs show challenging boundary conditions due to which minor adjustments in fuel costs will not affect the investment timeline substantially. Past this particular threshold the transformation strategies experience sudden and significant changes in their makeup. The inflection pattern allows both operators and analysts to easily identify cost conditions that force strategy reevaluation.

One significant feature of the model involves structural sensitivity which produces synchronized modifications that affect numerous decision variables when altering input parameters. A modification in the degradation rate affects every aspect of the retirement and acquisition operations and operational equilibrium throughout the complete time span. Fleet decisions demonstrate integrated behavior through coordinated effects because an analytical framework expresses these logical connections mathematically.

The model behaviors show that the system operates under economic boundaries while being directed by the ordering and nature of uncertainty. The system reaches its cost minimum point when a dynamic adjustment process is used to adapt to the changing conditions that surround decisions. The parameters provide insufficient information to determine what represents the best choice. These components of fuel trends, policy shapes, degradation profiles and emission penalties determine together the decision maze through their combined effects. The model creates an adaptable visual representation showing how each variable distributes across the area it depicts.

# 7 CONCLUSION and FUTURE WORK

Planning the shift from the traditional to electric cars fleet is no longer about separate cost benefit analysis. It is evolved into complex decision-making process from the meter of timing, uncertainty, policy design, and operational reliability. The model investigated in this paper is the model that directly addresses that complexity, providing a mathematical structure that enables the all these influencing factors to be taken into account at the same time rather than in isolation. Its power is in its ability to grab the conditions that change character fleet management over the longer-term—how much to invest, but when, and under which of conditions.

Through integrating the application of scenario-based pricing, variations-aware execution modelling, pollution beating specifics and time-sensitive incentives for the policy, the framework designs a place were real world constraint and strategic operations crossroads. The model is undeveloped to any virtue apparatus or geography, which donations to its relevance in both theoretical and practical contexts. It offers a straightforward structure for academic researchers to expose temporally distant resource allocation under uncertainty. For practitioners it is a tool enabling strategy design be tested without having to rely on full data or unrealistic assumptions.

Also, several Appendices can develop from this basis. Introducing stochastic representations of vehicle lifetimes, as an example, is a way to better represent uncertainty around asset performance and failure rates. Including uncertain or time-varying demand may more accurately model the operational issues faced by logistics networks or public transportation systems, in which capacity needs are not fixed. A possible extension would be to simulate mixed fleets that include not only BEVs but also other alternatives, like hydrogen fuel cell ones, with mileage costs and infrastructure required different from those of BEVs.

All of these extensions will require extra panache, but none would dismantle the basic structure. This current formulation was intended to allow instead for layers to be feasible to go on without rewriting the core logic of it. That flexibility makes it well-suited for future work in both the academic and policy-facing dimensions of transport planning.

## REFERENCES


[1] J. Hu, H. Morais, T. Sousa, and M. Lind, "Electric vehicle fleet management in smart grids: A review of services, optimization and control aspects," *Renewable and Sustainable Energy Reviews,* vol. 56, pp. 1207-1226, 2016.

[2] J.-P. Futalef, D. Muñoz-Carpintero, H. Rozas, and M. E. Orchard, "An online decision-making strategy for routing of electric vehicle fleets," *Information Sciences,* vol. 625, pp. 715-737, 2023.

[3] K. Seddig, P. Jochem, and W. Fichtner, "Integrating renewable energy sources by electric vehicle fleets under uncertainty," *Energy,* vol. 141, pp. 2145-2153, 2017.

[4] T. Chen, B. Zhang, H. Pourbabak, A. Kavousi-Fard, and W. Su, "Optimal routing and charging of an electric vehicle fleet for high-efficiency dynamic transit systems," *IEEE Transactions on Smart Grid,* vol. 9, no. 4, pp. 3563-3572, 2016.

[5] S. A. Qadir, F. Ahmad, A. M. A. Al-Wahedi, A. Iqbal, and A. Ali, "Navigating the complex realities of electric vehicle adoption: A comprehensive study of government strategies, policies, and incentives," *Energy Strategy Reviews,* vol. 53, p. 101379, 2024.

[6] C. R. Forsythe, K. T. Gillingham, J. J. Michalek, and K. S. Whitefoot, "Technology advancement is driving electric vehicle adoption," *Proceedings of the National Academy of Sciences,* vol. 120, no. 23, p. e2219396120, 2023.

[7] M. Amin, "Operational Management for "Electric Vehicle Charging Station (eV-Station)" In Indonesia," *Jurnal Ilmu Manajemen dan Bisnis,* vol. 14, no. 2, pp. 1-12.

[8] J. Nieto, P. E. Brockway, M. Sakai, and J. Barrett, "Assessing the energy and socio-macroeconomic impacts of the EV transition: A UK case study 2020–2050," *Applied Energy,* vol. 370, p. 123367, 2024.

[9] P. W. Panjaitan and G. Wang, "Designing Integrated EV Charging Station to Grid Platform," *International Journal,* vol. 11, no. 11, 2023.

[10] B. Loeb and K. M. Kockelman, "Fleet performance and cost evaluation of a shared autonomous electric vehicle (SAEV) fleet: A case study for Austin, Texas," *Transportation Research Part A: Policy and Practice,* vol. 121, pp. 374-385, 2019.

[11] J. A. Sanguesa, V. Torres-Sanz, P. Garrido, F. J. Martinez, and J. M. Marquez-Barja, "A review on electric vehicles: Technologies and challenges," *Smart Cities,* vol. 4, no. 1, pp. 372-404, 2021.

[12] K. S. Garud, S.-G. Hwang, J.-W. Han, and M.-Y. Lee, "Performance characteristics of the direct spray oil cooling system for a driving motor of an electric vehicle," *International Journal of Heat and Mass Transfer,* vol. 196, p. 123228, 2022.

[13] Y. Cao, L. Huang, Y. Li, K. Jermsittiparsert, H. Ahmadi-Nezamabad, and S. Nojavan, "Optimal scheduling of electric vehicles aggregator under market price uncertainty using robust optimization technique," *International Journal of Electrical Power & Energy Systems,* vol. 117, p. 105628, 2020.

[14] A. Alahyari, M. Ehsan, and M. Mousavizadeh, "A hybrid storage-wind virtual power plant (VPP) participation in the electricity markets: A self-scheduling optimization considering price, renewable generation, and electric vehicles uncertainties," *Journal of Energy Storage,* vol. 25, p. 100812, 2019.

[15] X. Zhang, X. Bai, and J. Shang, "Is subsidized electric vehicles adoption sustainable: Consumers' perceptions and motivation toward incentive policies, environmental benefits, and risks," *Journal of Cleaner Production,* vol. 192, pp. 71-79, 2018.

[16] X. Liu, X. Sun, H. Zheng, and D. Huang, "Do policy incentives drive electric vehicle adoption? Evidence from China," *Transportation Research Part A: Policy and Practice,* vol. 150, pp. 49-62, 2021.

[17] J. Vuelvas, F. Ruiz, and G. Gruosso, "A time-of-use pricing strategy for managing electric vehicle clusters," *Sustainable Energy, Grids and Networks,* vol. 25, p. 100411, 2021.

[18] P. Aliasghari, B. Mohammadi-Ivatloo, and M. Abapour, "Risk-based scheduling strategy for electric vehicle aggregator using hybrid Stochastic/IGDT approach," *Journal of Cleaner Production,* vol. 248, p. 119270, 2020.

[19] M. Schmidt, P. Staudt, and C. Weinhardt, "Decision support and strategies for the electrification of commercial fleets," *Transportation Research Part D: Transport and Environment,* vol. 97, p. 102894, 2021.

[20] J. Di Filippo, N. Nigro, and C. Satterfield, "Federal fleet electrification assessment," 2021.

[21] R. Ghotge, Y. Snow, S. Farahani, Z. Lukszo, and A. van Wijk, "Optimized scheduling of EV charging in solar parking lots for local peak reduction under EV demand uncertainty," *Energies,* vol. 13, no. 5, p. 1275, 2020.

[22] W. Yin, D. Mavaluru, M. Ahmed, M. Abbas, and A. Darvishan, "Application of new multi-objective optimization algorithm for EV scheduling in smart grid through the uncertainties," *Journal of Ambient Intelligence and Humanized Computing,* vol. 11, no. 5, pp. 2071-2103, 2020.

[23] J. Hagman, S. Ritzén, J. J. Stier, and Y. Susilo, "Total cost of ownership and its potential implications for battery electric vehicle diffusion," *Research in Transportation Business & Management,* vol. 18, pp. 11-17, 2016.

[24] R. Cuenca, L. Gaines, and A. Vyas, "Evaluation of electric vehicle production and operating costs," Argonne National Lab., IL (US), 2000.

[25] L. Mitropoulos, K. Kouretas, K. Kepaptsoglou, and E. Vlahogianni, "Developing a Total Cost of Ownership Model for Semi-Automated, Automated and Electric Vehicles," *SN Computer Science,* vol. 3, no. 4, p. 322, 2022.
[26] C. Hull, J. Wust, M. Booysen, and M. McCulloch, "Techno-economic optimization and assessment of solar-battery charging station under grid constraints with varying levels of fleet EV penetration," *Applied Energy,* vol. 374, p. 123990, 2024.
[27] A. Nurdiawati and T. K. Agrawal, "Creating a circular EV battery value chain: End-of-life strategies and future perspective," *Resources, Conservation and Recycling,* vol. 185, p. 106484, 2022.
[28] Y. S. Liu, M. Tayarani, F. You, and H. O. Gao, "Bayesian optimization for battery electric vehicle charging station placement by agent-based demand simulation," *Applied Energy,* vol. 375, p. 123975, 2024.
[29] L. Adenaw and M. Lienkamp, "Multi-criteria, co-evolutionary charging behavior: An agent-based simulation of urban electromobility," *World Electric Vehicle Journal,* vol. 12, no. 1, p. 18, 2021.
[30] J. J. G. Vilchez and P. Jochem, "Simulating vehicle fleet composition: A review of system dynamics models," *Renewable and Sustainable Energy Reviews,* vol. 115, p. 109367, 2019.
[31] C. Ledna, M. Muratori, A. Brooker, E. Wood, and D. Greene, "How to support EV adoption: Tradeoffs between charging infrastructure investments and vehicle subsidies in California," *Energy Policy,* vol. 165, p. 112931, 2022.
[32] C. Quinton, "The Impact of Government Subsidies on EV Manufacturers," Liberty University, 2024.
[33] H. Wang, Y. Jia, M. Shi, P. Xie, C. S. Lai, and K. Li, "A hybrid incentive program for managing electric vehicle charging flexibility," *IEEE Transactions on Smart Grid,* vol. 14, no. 1, pp. 476-488, 2022.
[34] Y.-C. Wu and E. Kontou, "Designing electric vehicle incentives to meet emission reduction targets," *Transportation Research Part D: Transport and Environment,* vol. 107, p. 103320, 2022.
[35] A. A. Visaria, A. F. Jensen, M. Thorhauge, and S. E. Mabit, "User preferences for EV charging, pricing schemes, and charging infrastructure," *Transportation Research Part A: Policy and Practice,* vol. 165, pp. 120-143, 2022.
[36] P. González-Aliste, I. Derpich, and M. López, "Reducing urban traffic congestion via charging price," *Sustainability,* vol. 15, no. 3, p. 2086, 2023.
[37] M. Pertl, F. Carducci, M. Tabone, M. Marinelli, S. Kiliccote, and E. C. Kara, "An equivalent time-variant storage model to harness EV flexibility: Forecast and aggregation," *IEEE transactions on industrial informatics,* vol. 15, no. 4, pp. 1899-1910, 2018.
[38] S. Moon and D.-J. Lee, "An optimal electric vehicle investment model for consumers using total cost of ownership: A real option approach," *Applied Energy,* vol. 253, p. 113494, 2019.
[39] C. Luo, Y.-F. Huang, and V. Gupta, "Dynamic pricing and energy management strategy for EV charging stations under uncertainties," *arXiv preprint arXiv:1801.02783,* 2018.
[40] S. M. Arif, T. T. Lie, B. C. Seet, S. Ayyadi, and K. Jensen, "Review of electric vehicle technologies, charging methods, standards and optimization techniques," *Electronics,* vol. 10, no. 16, p. 1910, 2021.

[41] C. Zhang, Y. Liu, Y. Qian, and H. Bao, "An optimization framework of electric vehicle (EV) batteries for product eco-design," *Procedia CIRP,* vol. 90, pp. 366-371, 2020.
[42] J. Guo, J. Yang, Z. Lin, C. Serrano, and A. M. Cortes, "Impact analysis of v2g services on ev battery degradation-a review," *2019 IEEE Milan PowerTech,* pp. 1-6, 2019.
[43] Y. Zhang *et al.*, "Performance assessment of retired EV battery modules for echelon use," *Energy,* vol. 193, p. 116555, 2020.