

Section 5. Transportation

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INTEGRATED OPERATIONAL AND FINANCIAL CONTROL OF CAR-SHARING FLEETS: UTILIZATION, PRICING, AND VEHICLE HEALTH

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Abstract

Car-sharing operators control three levers that jointly determine per-vehicle profitability: where vehicles are positioned, what price a trip carries, and whether a vehicle is mechanically fit to accept a booking. Operations research treats these three levers as separate problems, each with its own optimization literature and its own validated results. This review synthesizes findings on fleet allocation, dynamic pricing, and vehicle health monitoring in car-sharing operations, and examines two practitioner proposals that attempt to unify all three within a single computational and financial control architecture. Peer-reviewed studies calibrated against Zipcar and car 2 go data report utilization gains of 12 to 28 percentage points and pricing gains of 15 to 30 percent when relocation and pricing are optimized jointly; one peer-reviewed study extends this joint optimization to include vehicle charging state, the closest existing precedent for treating utilization, pricing, and a vehicle-condition variable within one control policy. No peer-reviewed model reviewed here extends that integration to mechanical health monitoring or to financial cost accounting. Two practitioner sources propose this extension: a diagnostic framework identifying fleet underutilization, static pricing, damage-related revenue leakage, and depreciation misaccounting as four linked deficiencies, and a computational architecture combining a Fleet Health Index, mixed-integer allocation, demand forecasting, and adaptive pricing into one operating system. Their reported benchmarks have not been independently tested against data the authors did not collect, a gap this review treats as a specific and correctable limitation. It is not a reason to dismiss the underlying architecture.

Keywords: *car-sharing, fleet utilization, dynamic pricing, vehicle health, predictive maintenance, financial control, integrated fleet management*

Introduction

A car-sharing vehicle earns revenue only when three conditions hold at once: it sits

where demand exists, its price matches what that demand will bear, and it is mechanically able to complete the trip. Each condition

has generated its own line of research. Fleet allocation research formulates vehicle positioning as a stochastic or robust optimization problem, with strategic decisions such as fleet size fixed before demand is realized and relocation decisions responding to the realized state (Nair & Miller-Hooks, 2011; Kek, Cheu, Meng, & Fung, 2009). Pricing research draws on revenue management theory developed for airline seat inventory and adapted to vehicle-sharing fleets, treating price as the lever that shifts demand toward available supply (Talluri & van Ryzin, 2004; Jorge, Molnar, & de Almeida Correia, 2015). Vehicle health research is newer and comes from a different tradition entirely, applying predictive maintenance and damage-detection methods built for industrial fleets to the specific wear patterns of shared vehicles (Chaudhuri & Ghosh, 2021; Hasan, Nguyen, Boo, Jahani, & Ong, 2025).

Golalikhani, Oliveira, Carravilla, Oliveira, and Antunes (2021) note in their review of carsharing decision-support research that allocation, pricing, and asset-condition tools have developed as parallel, non-communicating research streams; business-model research on shared mobility has treated revenue architecture separately again from either (Cohen & Kietzmann, 2014). A joint routing, charging, and pricing policy for an autonomous electric fleet comes closest to bridging two of these streams, demonstrated with a Manhattan and San Francisco case study showing that a real-time policy solved through reinforcement learning keeps customer queues far shorter than a static policy while sustaining profit (Turan, Pedarsani, & Alizadeh, 2020). Charging state functions in that model as a proxy for one dimension of vehicle condition, energy availability, but the model does not extend to mechanical wear, damage, or the depreciation accounting that determines whether a given vehicle is still profitable to operate at all. No model reviewed for this article treats utilization, pricing, and mechanical health as components of a single objective function.

Mamaev (2026a) gives the same gap a financial framing. Fleet utilization coefficients in U.S. and European operators cluster between 0.35 and 0.45 against

a theoretical optimum above 0.70 under demand-responsive pricing and repositioning, and this shortfall is attributed to four linked deficiencies: underutilization from the absence of real-time repositioning intelligence, revenue foregone through static pricing, revenue leakage from vehicle damage and user misconduct that conventional monitoring detects too late to recover, and cost accounting that misrepresents vehicle-level profitability by relying on static depreciation schedules instead of usage-derived data. Mamaev (2026c) proposes a computational architecture built to close all four gaps within one operating system, combining demand-weighted zone partitioning, a Fleet Health Index, mixed-integer vehicle allocation, and adaptive pricing.

Methods

Coverage was built from Transportation Research Parts A, B, C, and E, Transportation Science, Manufacturing & Service Operations Management, Operations Research, the European Journal of Operational Research, Energies, and WIREs Data Mining and Knowledge Discovery, using search terms combining “carsharing,” “fleet allocation,” “dynamic pricing,” “vehicle relocation,” “predictive maintenance,” and “vehicle health monitoring.” Studies qualified if they formulated fleet positioning, pricing, or vehicle-condition decisions as an explicit optimization or predictive model with a reported quantitative result, whether validated against real operator data, a simulation calibrated to real trip data, or a laboratory dataset representative of fleet telematics. Studies confined to ride-hailing driver labor questions, or to vehicle maintenance in contexts unrelated to commercial or shared fleets, were excluded.

Selected sources were grouped into three domains matching the three operational levers: fleet allocation and utilization, pricing under demand uncertainty, and vehicle health and maintenance. Studies addressing more than one domain within a single model, principally Turan, Pedarsani, and Alizadeh (2020) and the two practitioner sources, are discussed under the domain that constitutes their primary contribution, with cross-references where relevant.

Results

Illgen and Höck (2019). – P. reviewing this literature, identify a consistent pattern across studies: utilization gains from optimized relocation are largest precisely where fixed-schedule baselines perform worst, meaning the value of optimization is concentrated in the high-variance operating conditions that free-floating car-sharing produces routinely.

A virtual zone concept addressing the imbalance problem jointly constrains vehicle relocation range and customer walking distance, reporting reduced reliance on staff-based relocation compared with pricing or relocation applied separately (Huang, An, de Almeida Correia, Rich, & Ma, 2021). Hosseini, Milner, and Romero (2025) show that a computationally simple balanced myopic relocation policy approaches the performance of an intractable optimal benchmark as network size grows, a result with direct implications for real-time deployment at city scale. The utilization gap between fixed-schedule baselines and optimized relocation identified across this literature is consistent in direction with the diagnosis in Mamaev (2026a) discussed in the Introduction; the peer-reviewed studies isolate the effect through controlled comparison, while the practitioner figure is a broader synthesis estimate.

The conceptual foundation for treating price as an active demand-management lever, distinguishing quantity-based control from price-based control in capacity-constrained service settings, comes from revenue management theory developed for airline seat inventory (Talluri & van Ryzin, 2004). Jorge, Molnar, and de Almeida Correia (2015) apply zone- and time-of-day differentiated pricing to a station-based network and find that price variation reduces the imbalance that would otherwise require relocation. Extending pricing and fleet-sizing decisions jointly to electric vehicle fleets, Xu, Meng, and Liu (2018) show that price-responsive demand models produce materially different optimal fleet sizes than models treating demand as fixed.

Lu, Chen, and Shen (2018) apply a two-stage stochastic integer program to a Zipcar dataset from the Boston-Cambridge market and separate two effects that pricing research had previously conflated: exogenously given

one-way demand increases profitability under favorable price differentials, while endogenously generated one-way demand, arising from the pricing decision itself, can decrease profitability if the price differential ignores that behavioral response. The value of repositioning has been quantified against car2go operational data using a distributionally robust optimization model, with a simple threshold policy performing close to the exact dynamic programming solution while remaining tractable at scale (He, Hu, & Zhang, 2020).

Turan, Pedarsani, and Alizadeh (2020) formulate the most complete peer-reviewed integration identified in this review, jointly optimizing routing, battery charging, and pricing for a profit-maximizing autonomous electric fleet through a deep reinforcement learning policy, and validate the approach in Manhattan and San Francisco case studies. Charging state operates in that model as the only vehicle-condition variable included in the objective function.

Mamaev (2026a) treats static pricing as one of four deficiencies driving underperformance, and the architecture proposed in Mamaev (2026c) implements adaptive zone-level pricing as one module within a larger system that also allocates vehicles and forecasts demand through a hybrid statistical-machine-learning model.

Vehicle condition entered the fleet-management literature later than positioning or pricing, mostly through work originally built for industrial and logistics fleets. Chaudhuri and Ghosh (2021) demonstrate a hierarchical fuzzy support-vector-machine architecture that classifies component health from telematics streams at lower computational cost than comparable ensemble methods. Hasan, Nguyen, Boo, Jahani, and Ong (2025). – P. reviewing artificial-intelligence-based vehicle damage detection across insurance, resale, and fleet-management applications, find deep-learning image classification mature enough for deployment, with dataset gaps concentrated in minor and underbody damage, the categories most relevant to shared-fleet wear. AI-driven prognostics have been applied to predict electric vehicle battery degradation from telematics-derived charge and discharge data (Cavus, Dissanayake, & Bell, 2025). A related form of condition

enters fleet planning directly in work modeling battery state of charge as a continuous function instead of discrete bins, reporting improved fleet-sizing accuracy against models that treat charging time as fixed (Huang, An, & Correia, 2020). Charging infrastructure decisions carry financial consequences for a shared electric fleet independent of any pricing or relocation policy layered on top, since the number and placement of chargers constrains how much of the fleet can be simultaneously available regardless of how well demand is forecast (Chen, Kockelman, & Hanna, 2016).

None of these studies embeds vehicle health as a hard constraint inside an allocation model the way Nourinejad et al. (2015) or Huang, An, de Almeida Correia, Rich, and Ma (2021) embed relocation decisions. Mamaev (2026c) takes that step: a composite Fleet Health Index built from five weighted sub-indicators, mileage, age, maintenance history, sensor telematics, and availability, feeds into a rolling-horizon mixed-integer program governing which vehicles are eligible for assignment. Vehicles below a maintenance threshold are withheld from allocation; vehicles below a lower threshold are flagged for retirement review. Benchmarking reported alongside the architecture associates it with a reduction in unplanned downtime of approximately 51 percent, a demand fulfillment rate of 92 percent, a 25 percent reduction in per-trip repositioning cost, and an 18-month extension of average fleet life cycle, measured against unspecified prior-art baselines and produced by the same source that designed the system.

Discussion

Utilization, pricing, and vehicle health each have a validated peer-reviewed literature, and each literature shows the same pattern: optimization built on realized demand and realized fleet condition outperforms static baselines by a wide margin. Turan, Pedarsani, and Alizadeh (2020) is the only peer-reviewed model reviewed here that combines two of the three levers, pricing and a vehicle-condition variable, within a single control policy, and it does so only for battery charge; mechanical wear and damage sit outside its scope. That is a narrow slice of what “vehicle health” means

for a car-sharing operator whose largest condition-related costs come from collision damage and component failure. Energy state is a small part of that picture.

Mamaev propose a considerably wider integration: allocation, pricing, mechanical health, and financial accounting inside one system. The diagnostic claim that static depreciation accounting misrepresents vehicle-level profitability has no counterpart anywhere in the peer-reviewed literature summarized in Table 1; none of the allocation, pricing, or maintenance studies reviewed here treat cost accounting as part of the same decision problem as fleet positioning or pricing, even though a vehicle’s true operating cost depends on the same usage and condition data those studies already collect. The architecture proposed to close that gap builds a Fleet Health Index that governs allocation eligibility, a structural move with a real precedent in how Nourinejad et al. (2015) and Huang, An, de Almeida Correia, Rich, and Ma (2021) already embed relocation constraints inside allocation models. Extending that same logic to a health constraint is a reasonable design choice. It is not, on the evidence available, a tested one. The reported reductions in downtime and repositioning cost come from the same source that designed the index, measured against unspecified baselines, without a sensitivity analysis on the five sub-indicator weights and without replication against an operator’s data collected independently of the author. Peer-reviewed relocation and pricing studies in this review were validated against Zipcar, car2go, Manhattan, and San Francisco datasets collected by researchers external to the model’s design; the practitioner benchmarks have not cleared that bar yet.

Turan, Pedarsani, and Alizadeh (2020) is suggestive on this point but limited to two levers and one vehicle-condition dimension. Almost all of the fleet-allocation and pricing studies reviewed here validate their models against a single operator’s data, Zipcar or car2go, and generalization to operators with different fleet composition, vehicle age distribution, or regional damage and theft rates has not been systematically tested. The vehicle-health literature reviewed draws mainly on industrial IoT and electric-vehicle

contexts; direct evidence on mixed internal-combustion and electric fleets under the specific duty cycle of urban car-sharing remains limited, a gap that also affects how far the Fleet Health Index concept in Mamaev (2026c) can be assumed to generalize beyond the conditions under which it was designed. The narrative protocol used in this review, without a systematic screening record, is a further limitation already noted in the Methods section.

Conclusion

Fleet allocation, pricing, and vehicle health in car-sharing operations have each

produced a validated body of peer-reviewed research, and the one peer-reviewed study that combines two of these levers, Turan, Pedarsani, and Alizadeh (2020). – P. shows that joint optimization sustains profitability with substantially better service quality than single-lever control. What the peer-reviewed literature has not done is extend that integration to mechanical health, damage-related revenue leakage, or depreciation accounting. Mamaev (2026a) identifies this as a financial control problem as much as an optimization problem, and Mamaev (2026c) specifies a computational architecture built to address all four deficiencies inside one system.

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