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EDITORIAL

Revenue management for complex systems

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Revenue Management (RM) and Pricing have a long tradition of elegant mathematical formulations, typically as large-scale stochastic dynamic programs, see, for instance, Gallego and van Ryzin (1994), Talluri and van Ryzin (1998), or Talluri and van Ryzin (2004). These models capture, in full generality, the trade-offs among capacity, uncertainty, and customer choice that define RM. Yet, as already noted by Talluri and van Ryzin (1998), the resulting problems are often simply too large to solve exactly. The enduring challenge, therefore, lies not in formulating the "perfect" model but in extracting useful, implementable decision policies from systems that defy exact optimization.

This Special Issue on Revenue Management for Complex Systems brings together five contributions that embody precisely this philosophy. Each paper begins with a theoretically sound model that captures the richness of real-world complexity (multi-dimensional heterogeneity, dynamic decisions under uncertainty, coupled subsystems, and data-driven learning) but then forges a computational path that makes the model tractable and actionable. Although they operate across diverse domains from pricing consumer products to managing transportation, logistics, and mobility networks, they share a unifying spirit: to turn complexity into structure, and structure into insight.

Dynamic Nonlinear Pricing under Multiunit Demand

When customers differ not only in their willingness to pay but also in the quantity they demand, even the simplest dynamic pricing problems become analytically

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intractable. Schur (2025) tackles this challenge by unifying nonlinear and dynamic pricing under a model of two-dimensional customer heterogeneity, one dimension for value perception, another for consumption intensity. The resulting stochastic control problem is theoretically exact but computationally infeasible. The paper derives structural properties of the optimal solution and introduces a set of near-optimal heuristics that are orders of magnitude faster while retaining most of the potential revenue gains. Interestingly, a simple piecewise-linear pricing rule (one price for the first unit, another for add-ons) emerges as a powerful practical compromise. The contribution exemplifies how RM can distill complex behavioral heterogeneity into implementable tariffs that remain interpretable and robust in dynamic settings.

Ancillary Revenue and Capacity Coupling in Transportation

A similar theme of balancing analytical rigor with tractability is explored in Barz et al. (2025), who study ancillary revenues from extra seat reservations in passenger transportation. Customers may choose to purchase an adjacent seat for additional comfort, effectively doubling the capacity consumed per transaction. This feature transforms the classical single-leg seat allocation problem into a network problem, where standard fare and ancillary offers compete for shared inventory under correlated demand. The authors formalize the exact dynamic program and show that it rapidly becomes unsolvable in its full form. They then develop a hierarchy of approximations through upper bounds from deterministic relaxations and decomposition-based heuristics, that deliver various revenue-to-runtime trade-offs. Beyond computational ingenuity, the paper illustrates how RM principles can guide design choices for ancillary services, transforming what might appear as ad hoc product differentiation into a coordinated capacity-control policy.

Dynamic Compensation for Last-Mile Logistics

While the first two papers focus on product pricing, Schur and Winheller (2025) extend RM thinking into the realm of on-demand logistics. In crowdshipping and occasional-driver delivery systems, decision makers must dynamically assign tasks and compensations to a stochastic stream of potential drivers, each with individual preferences and availability. Here, the challenge lies not in pricing products to customers but in pricing tasks to agents. The authors cast this as a dynamic program and develop approximation schemes. The resulting mechanism adjusts payments based on anticipated future supply and demand, achieving a balance between cost efficiency and service reliability. The work demonstrates the versatility of RM principles as a general framework for managing matching, incentives, and scarce resources in human-centric logistics networks.

Learning-Based Network Revenue Management

The issue then transitions from analytical approximations to learning-based approaches. In Hausenblas et al. (2025), the focus returns to the canonical network RM problem. Rather than solving the problem via simulation or online experimentation, the authors apply offline reinforcement learning (RL) to learn pricing policies directly from historical data. Their algorithm adapts actor-critic methods to handle state-dependent action sets typical in RM, and learns improved policies that dominate the behavior policy used to generate the data. The result is a scalable controller that can be deployed without the risk of online exploration. Conceptually, this marks an important evolution in RM: data replaces explicit system models as the main source of structure. The paper thus bridges the gap between machine learning and classical operations research, showing how the two paradigms can cooperate rather than compete.

Demand Management in Rural Shared Mobility

Finally, Anzenhofer et al. (2025) expand the reach of RM to a domain that is both operationally and socially complex: rural shared mobility-on-demand systems. In sparsely populated areas, ride requests are irregular and geographically dispersed, making pooling inefficient and unprofitable. The authors formulate the system as a Markov decision process that controls availability, deciding when and where to offer rides, to balance utilization, service quality, and financial sustainability. They test a spectrum of policies, from myopic to anticipatory, on real-world FLEXIBUS data and provide managerial insights on the trade-offs among profitability, coverage, and fairness. The work reframes rural mobility as a governed stochastic system, where RM-style demand management provides a policy layer that coordinates economic and social objectives. It exemplifies how RM methods can serve as decision intelligence tools in public-sector and sustainability-driven contexts.

Looking Ahead: Complexity, Tractability, and the Evolution of Revenue Management

Taken together, the five contributions showcase how RM has evolved into a general theory of decision-making under complexity. Each paper starts from a model that, in its full generality, is computationally prohibitive. Through heuristics, decompositions, approximations, and learning-based methods, the authors craft decision strategies that are implementable, interpretable, and empirically near-optimal. The unifying methodological insight is that complexity should not be avoided but structured and managed. Whether through dimensionality reduction, decomposition, or data-driven learning, each approach transforms an unsolvable stochastic system into a controllable one. Beyond methodology, these papers reflect the breadth and adaptability of modern RM. The discipline has moved far beyond its origins in airline seat control and hotel pricing. Today, it governs logistics platforms, mobility systems, and even hybrid human–machine markets. The same principles i.e., scarcity, uncertainty, and dynamic control reappear in increasingly varied forms. RM thus provides a language for complex socio-technical systems, where pricing, availability, and incentives act as control variables that coordinate decentralized actors toward efficient outcomes. Complexity, in this sense, is not a flaw but a defining feature of real decision environments. The contributions gathered in this issue demonstrate that embracing computational strategies rather than retreating from them allows us to expand the practical frontier of RM. By uniting structural insights from classical OR with learning and data-driven adaptability, these works collectively point toward a future where RM becomes the operational layer of complex systems turning data, behavior, and uncertainty into actionable decisions. We hope that the papers in this Special Issue will inspire further exploration of RM as a bridge between modeling and practice, between theory and computation, and between economic efficiency and system design.

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