

CASE STUDY / AUTOMATED VEHICLE ORDERING

The Order Mix the Factory Can Actually Build

Linking demand prediction to constrained decisions about vehicle configurations

EXECUTIVE CONCLUSION

Predicting desirable vehicles is only half the problem. Manufacturing a profitable combination requires portfolio-level optimization.

\$64M

incremental profit, project-reported

3 mo.

order horizon

ML + MILP

demand model feeding an order optimizer

Founder-led prior industry project; not delivered by Bit Bros LLC. The \$64M amount is project-reported rather than independently audited.

The problem: popular is not always buildable

An automotive manufacturer must choose a feasible collection of models, trims, options, and colors before customer demand is fully known. A prediction model can estimate which configurations buyers will prefer. But independent rankings are not a production plan: multiple highly ranked vehicles may consume the same limited components, violate factory restrictions, or produce the wrong regional mix.

The project combined tree-based demand modeling and mathematical optimization to formulate a roughly three-month order recommendation. Demand estimates informed the economics of candidate configurations, while the optimizer selected a buildable portfolio under manufacturing and supply constraints. The project lead reported approximately \$64 million in incremental profit.

THE DECISION TO IMPROVE

Which combinations of vehicle configurations should be ordered over the next three months, given predicted demand, component constraints, plant restrictions, and financial priorities?

1. Convert demand signals into economic choices

A forecast ranking does not resolve shared scarcity

Suppose configuration A earns \$1,100 of expected contribution but consumes two units of a scarce option. Configuration B earns \$800 and consumes one unit. This month 300 option units are available, and the demand model predicts 120 buyers for A and 200 for B. These figures are synthetic illustrations, not measurements from the project.

	Rank per vehicle	Optimized order
Vehicles of A	120	50
Vehicles of B	60	200
Option units used	300	300
Contribution	\$180K	\$215K

Ranking by contribution per vehicle orders all the A that demand supports. The optimized order favors B, which earns \$800 per option unit against A's \$550, and earns 19.4% more from the same supply while also building more vehicles.

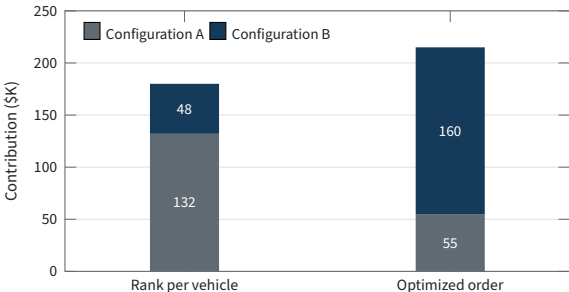


Exhibit 1. Contribution by configuration under each order, from the same 300 option units: \$180K against \$215K.

With one scarce option, ranking by contribution per option unit would find this answer. Real orders share many options, plant limits, and mix rules at once, so no single ranking holds.

The optimizer must compare whole portfolios. A choice that looks good for one vehicle may eliminate several attractive alternatives elsewhere in the order. This is exactly the type of coupling for which mixed-integer optimization is designed.

Represent decisions explicitly

Let x_{it} be the number of units of configuration i ordered for period t , with estimated incremental contribution v_{it} . The simplified model is

$$\max_{x \in \mathbb{Z}_+} \sum_{i,t} v_{it} x_{it} \quad \text{s.t.} \quad Ax \leq b, \quad L \leq Bx \leq U.$$

The matrices capture shared resource capacity and product-mix rules. This is a teaching abstraction; the original proprietary problem included additional operational detail. The essential distinction is between the predictive component producing economic signals and the prescriptive component finding a feasible allocation.

2. Make the constraint system legible

Decision input	What it contributes
Predicted demand	Relative value of possible configurations
Configuration catalog	Compatible models, trims, colors, and options
Factory limits	Feasible production amounts and build locations
Supplier capacity	Shared scarcity across competing orders
Business policy	Approved regional, product, and mix requirements
Order cadence	How decisions are revised over three months

Inherited rules require scrutiny. A factory limit is physical; a preferred share for a color or trim may represent a commercial objective. Translating every preference into a hard constraint can overconstrain the order and sacrifice economic value. Better designs attach accountable owners to each rule and distinguish infeasibility from unfavorable economics.

Treat substitutions as full-portfolio decisions

If an option becomes unavailable, the model should identify which alternative order produces the highest remaining contribution. If a region overrides a recommendation, the system should explain which configuration or resource allocation changed, and what opportunity cost accompanied the override.

REFERENCE WORKFLOW

Demand estimates → economics and catalog → plant and supplier limits → portfolio MILP → planner review and approved orders

3. Evaluate the order, not only the prediction

Forecast error matters, but the objective is a good set of orders. Two forecasts can have similar accuracy and produce different decisions near a supplier bottleneck. Conversely, a substantial accuracy improvement may have little value when it leaves the preferred feasible portfolio unchanged.

Useful measures include expected and realized contribution, feasibility rate, recommendation acceptance, rejected configurations, allocation of scarce components, and the stability of the order mix under plausible forecast revisions. The same measurement framework can compare the optimization policy with existing planner and ranking-based baselines.

The project lead reported approximately \$64 million in incremental profit associated with the earlier automated ordering work. This case study cannot reproduce a full financial reconciliation or isolate the respective contributions of forecast accuracy, optimization, and process redesign. The project figure is consequently presented as reported impact, not a new audited Bit Bros claim.

4. Practical implementation lessons

Start with a narrow slice of the catalog and the resources that actually bind. Build a baseline using simple forecast ranking, then quantify where the global optimizer

improves the feasible order. Add product interactions, regional constraints, and governance in stages.

Test the mathematical model with known cases before introducing operational dashboards. Validate both sides of the pipeline: holdout quality of the predictive signals and economic quality of the resulting decisions under the same resource limits. Explicitly record order changes, exceptions, and reasons for overrides.

TRANSFERABLE LESSON

When several individually attractive recommendations compete for the same resources, the business needs an optimization of the complete decision portfolio.

5. What we would add to a modern version

The same structure supports a stronger decision system. Each addition should be tested against the current order policy rather than assumed to help.

Addition	Question it answers
Demand distributions	Does the order change when demand is a range, not a point?
Order simulation	How do lost sales, aging stock, and late changes play out over the horizon?
Override learning	Which planner changes improve on the model, and which cost money?
Value tracking	What did each order earn against a credible baseline?

A demand distribution matters most where configurations compete for a scarce option: ordering to the expected value of each one ignores that the costs of overbuying and underbuying are rarely equal. These are extensions, not claims

about the original project.

Further reading

Elmachtoub, A. N. and Grigas, P. Smart “predict, then optimize.” *Management Science* 68(1), 2022.

Williams, H. P. *Model Building in Mathematical Programming*, 5th ed. Wiley, 2013.

DeJans Jr., A. *The MILP Optimization Handbook*. Bit Bros, 2025.

About the case and Bit Bros

This paper draws on an automotive ordering project led by **Adam DeJans Jr.** in an earlier industry role. It was not a Bit Bros client engagement. The manufacturer, proprietary constraint data, and financial methodology are not disclosed. The reported profit figure is not represented as an audited realized outcome. Bit Bros LLC helps organizations connect predictive modeling, mathematical optimization, and operating decisions. We publish these field notes to explain the underlying choices and trade-offs without disclosing proprietary client assets.



Adam DeJans Jr.
Technical Managing Director, Bit Bros LLC
Decision scientist specializing in optimization, simulation, and decisions under uncertainty.

Design the decision. Make the trade-offs explicit.