

The Vehicle Mix Is an Economic Decision

How mathematical optimization helped an automotive planning team allocate scarce capacity across North America

EXECUTIVE CONCLUSION

A better production mix can unlock material value without requiring the planner to predict every future outcome perfectly.

Vehicle-production planning is a portfolio decision under binding resource constraints. Once those constraints are explicit, an optimizer can compare feasible mixes across products and periods and show where scarce capacity creates the most value. This case describes prior automotive work led by a Bit Bros partner: the decision architecture, the optimization design, and the lessons.

40,000

additional vehicles/year

\$390M

incremental profit estimate

24 mo.

planning horizon

200

vehicle types modeled (approx.)

Reported project figures from the project lead; the profit number is a project-reported estimate, not an independently audited realized outcome. Work was performed in an earlier industry role, not as a Bit Bros client engagement.

The planning problem

A North American automotive manufacturer must continually determine which vehicle types to produce, where, and when. Every feasible plan consumes assembly capacity, shared parts, labor, and supplier resources. Customer demand differs across products and periods, as do economics and environmental consequences. A vehicle mix that looks attractive in isolation may block a more valuable combination elsewhere in the network.

The same bottleneck can constrain many vehicle types at once, so a scarce slot given to one product is taken from another. That cost is rarely visible in a spreadsheet organized by model or plant.

The project addressed a long-horizon supply-allocation problem spanning approximately 24 months and around 200 vehicle types. The objective was to translate forecasts and operating constraints into a consistent production mix while accounting for profit, volume, and greenhouse-gas considerations.

THE DECISION

How should the business allocate limited production resources across vehicle types and future periods so that the resulting mix is feasible, economically attractive, and aligned with enterprise priorities?

1. Make the economics of the mix explicit

Capacity is valuable because of what it could produce instead

An unconstrained plan can simply chase expected demand. A constrained plan must rank competing uses of scarce resources. The economically relevant comparison is the incremental contribution of one alternative against the contribution forfeited by making that choice.

Consider two products that share a capacity bottleneck. Product A earns a higher contribution per unit, but uses more of the constrained resource. Product B earns less per unit but may yield higher contribution per constrained hour, or may support a strategic volume objective. Neither a demand ranking nor a unit-margin ranking necessarily identifies the best feasible mix.

A two-product illustration

Suppose a plant has 1,000 hours of a bottleneck operation per month. Product A contributes \$3,000 per unit and needs 2 bottleneck hours; product B contributes \$2,000 and needs 1 hour. Monthly demand is 400 units of A and 700 of B. The numbers are invented to show the mechanism; they are not project data.

	Rank by unit margin	Optimized mix
Units of A	400	150
Units of B	200	700
Bottleneck hours used	1,000	1,000
Contribution	\$1.60M	\$1.85M

Ranking by unit margin builds all the A that demand allows and fills the remaining hours with B. The optimized mix does the opposite, because B earns \$2,000 per bottleneck hour against A's \$1,500. The same capacity produces 15.6% more contribution, and more vehicles.

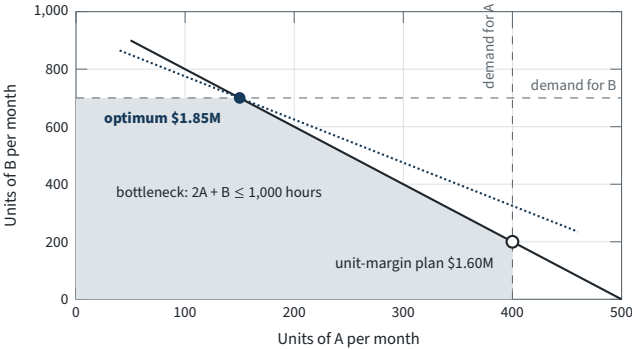


Exhibit 1. Feasible mixes (shaded) for the two-product illustration. The dotted line is every mix worth \$1.85M; no feasible mix lies above it.

With two products and one bottleneck, ranking by contribution per bottleneck hour would find the answer. A real network has hundreds of products and many shared resources at once, so no single ranking holds for all of them. That is the job a mathematical program does.

A practical decision model therefore needs a common set of variables and constraints. Let x_{ipt} denote vehicles of type i allocated to location p in period t . A simplified economic core is

$$\max_{x \in \mathbb{Z}_+} \sum_{i,p,t} m_{ipt} x_{ipt} \quad \text{s.t.} \quad Ax \leq b, \quad x \leq d,$$

where m_{ipt} is a contribution coefficient, $Ax \leq b$ represents coupled operational limits, and d bounds useful allocations using demand and other eligibility rules. This is a schematic illustration, not the original proprietary production formulation.

Business priorities are not interchangeable

Profit, throughput, customer demand coverage, and greenhouse-gas impact can conflict. The model must make these trade-offs visible and governed rather than hiding them in ad hoc business rules. The original project considered several enterprise objectives; a practical implementation may use prioritized objectives, explicitly approved trade-off weights, or scenario comparisons.

Objective	Planning question
Economic value	Which feasible mix creates the highest contribution?
Vehicle volume	How many total units can be built and delivered?
Demand alignment	Where does scarce supply best match customer need?
Emissions	How do product choices affect fleet-level targets?

2. Encode the physical system

The hard part is expressing shared constraints faithfully

Production allocation is difficult because vehicle types compete for the same limiting resources. A global model can capture these interactions without expecting every planner to manually coordinate every substitution.

Constraint family	Illustrative representation
Plant capacity	Maximum build quantities by facility and period
Shared components	Parts consumed jointly across multiple vehicle types
Product eligibility	What can physically be built in a given location
Demand / mix bounds	Market demand, minimums, maximums, and mix restrictions
Multi-period balance	Production and resource availability over time
Environmental limits	Aggregate requirements and product-specific impacts

A representative component constraint is

$$\sum_i a_{ikp} x_{ipt} \leq C_{kpt},$$

where a_{ikp} is resource k consumed per unit of product i at plant p , and C_{kpt} is the corresponding available capacity. In a real system these constraints interact across the full network, with rules for product compatibility, timing, and business policy.

A coherent global answer beats isolated local answers

A local spreadsheet can choose the best product for a single plant, month, or shortage. Yet a local improvement can create a worse outcome elsewhere by consuming a shared resource, violating a cross-period condition, or shifting emissions to a more constrained part of the plan.

A mixed-integer program evaluates those substitutions in a single economic framework, so every requested exception carries a visible opportunity cost. At this scale, transparent modeling and reliable data matter as much as the solver.

3. Treat the planner's workflow as part of the model

From inputs to an executable allocation recommendation

The useful system is the sequence of decisions around the optimizer. Forecasts and resource assumptions must be versioned; business rules must be traceable; infeasibilities must be explained; and the recommended mix must be reviewed and converted into an operating plan.

REFERENCE DECISION FLOW

Demand and economics → constraints → allocation MILP → scenarios and planner review → approved build mix

Planners need to see which constraint binds and why the mix changed; an objective value alone gives them no basis to challenge assumptions or accept a large shift.

Model quality also means decision stability

A long-horizon plan should remain interpretable when demand shifts or resource limits are updated. A tiny change in input assumptions should not casually trigger disruptive changes if comparable-value, more stable alternatives exist. This motivates explicit change penalties, scenario stress tests, and careful treatment of near-optimal plans when operational stability matters.

Optimization does not remove the need for governance: stakeholders still decide acceptable trade-offs and which constraints are physics, policy, or negotiable preference.

4. What the project reported

The project lead has previously reported a production-allocation improvement of approximately 40,000 additional vehicles per year and an incremental profit estimate of approximately \$390 million compared with the relevant planning baseline. These are project-reported figures and should be read with appropriate care: the paper does not claim an independent audit, a randomized causal evaluation, or a detailed public reconciliation from modeled value to realized financial statements.

Where the value comes from

The general mechanism behind this result is a better feasible product mix. When a constrained resource is allocated using a consistent objective, the planning system can direct production to combinations with stronger enterprise value while respecting the operational network. Even when production capacity is fixed, economic output can change materially because the allocation of that capacity changes.

Secondary benefits, such as fewer inconsistencies across planning teams and faster scenario testing, are real but unquantified here.

5. Lessons that transfer beyond automotive

Begin with the choice the organization must make

Technical teams should first define the allocation decision, time horizon, feasible actions, and economics. A forecast is useful only through its effect on those decisions. The best early discussion is often a concrete comparison: if one scarce build slot becomes available, what should the enterprise build, and why?

Classify rules before turning them into code

Physical constraints must hold. Legal or contractual constraints often must hold. Economic preferences generally belong in an objective or explicit trade-off. Historical conventions deserve scrutiny. Treating every planner preference as a hard constraint can protect yesterday's choices at the expense of tomorrow's value.

Invest in scenario comparison rather than false precision

Demand, supply, profitability, and policy targets change. The important question is how a proposed allocation performs over a useful range of plausible conditions. Scenarios expose the price of infeasibility, identify fragile bottlenecks, and prevent a single plan from acquiring more authority than its assumptions justify.

Explain trade-offs in the unit leaders actually manage

Leaders need volume, contribution, utilization, exceptions, and emissions. The solver gap matters to the model owner; decision owners need to know in business terms why the mix changed and what was given up.

A USEFUL EXECUTIVE DIAGNOSTIC

If every plant or product team is optimizing its own allocation independently, who is responsible for measuring the opportunity cost imposed on the rest of the enterprise?

6. What we would add to a modern version

The same modeling foundation supports a richer decision system. We would emphasize versioned probabilistic demand scenarios, a transparent economic objective, repeated simulation of replanning, and an auditable record of manual overrides. Each layer has a test: do distributional changes alter the preferred mix, can marginal trade-offs be explained, does the policy hold across plausible shocks, are overrides and trade-off approvals recorded, and is realized economic performance measured?

These are extensions, not claims about the original project; add each only when it improves the decision enough to justify its cost.

Further reading

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

Bertsimas, D. and Tsitsiklis, J. N. *Introduction to Linear Optimization*. Athena Scientific, 1997.

Powell, W. B. *Reinforcement Learning and Stochastic Optimization*. Wiley, 2022.

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

About the case and Bit Bros

This paper draws on automotive supply-allocation work led by Adam DeJans Jr. in an earlier senior industry role. It was not a Bit Bros client engagement. The manufacturer's identity, proprietary model, client data, and individual operational constraints are not disclosed. The mathematical examples are intentionally simplified to explain the decision architecture; they are not represented as production source code. Reported project metrics have not been independently verified for this publication. Bit Bros applies optimization, simulation, and decision science to operating problems, building systems that turn forecasts, constraints, and economics into repeatable decisions.



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Better decisions are built, not merely calculated.