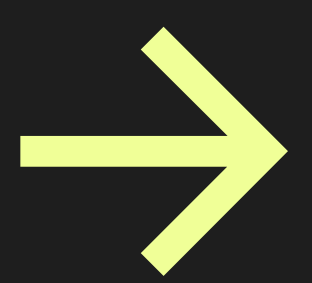




Solving the Shared Truckload Problem at Scale



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Intro



Transportation is modernizing. With a growing need to do more with less, and the rise of the sharing economy, businesses that find creative ways to participate cooperatively to make the most use out of shared logistics resources can reduce costs, improve service, and create more agile and flexible supply chains.

I. How Shared Truckload Works



Conceptually, Shared Truckload (STL) is simple - ridesharing of freight onboard hubless, truckload carrier capacity. Shippers pay only for the space they need, while carriers execute STLs without the use of intermediate cross docks or terminals, making one or more pickups and dropoffs along the way. **STL has benefits for both shippers and carriers:**



Shippers with small-to-mid-sized freight that would otherwise move as a full truckload (FTL) stand to reduce costs while maintaining the high service levels, low risk of damage, and expedited transit that truckload carriers provide.

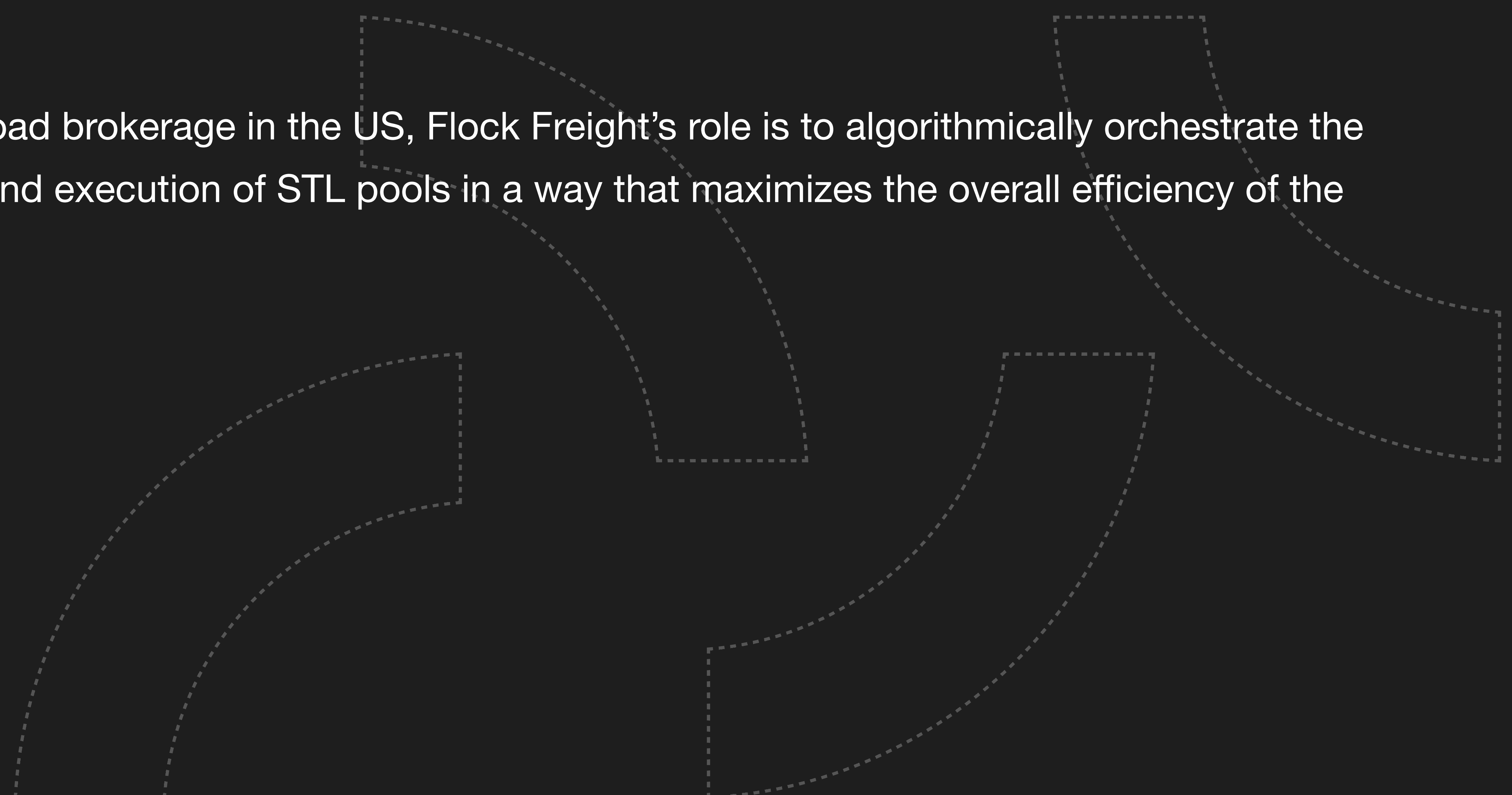


Shippers with freight that would otherwise move on-hub as a standard less-than-truckload (LTL) or volume less-than-truckload (VLTl) shipment can use Shared Truckload to access the lower damage rates, improved service and transit of truckload capacity without having to pay the full cost for exclusive use of a truckload carrier's vehicle.



Truckload carriers stand to earn more per mile executing STL pools than traditional FTL shipments because their trucks are often fuller.

As the largest Shared Truckload brokerage in the US, Flock Freight's role is to algorithmically orchestrate the identification, prioritization, and execution of STL pools in a way that maximizes the overall efficiency of the way freight moves.



II. Why it's a Hard Problem



At first glance, facilitating STL pools might seem as straightforward as integrating an off-the-shelf optimizer, (some of which are already available in popular Transportation Management Systems (TMS) software packages), into standard freight workflows. While tools like those can be a good starting point to help solve the underlying math problem for a single shipper, actually capitalizing on the full opportunity requires a solution that accounts for the operational nuances of enabling multiple shippers to participate in STL pools together. In the following sections, we highlight some of these challenges and outline how Flock's patented combination of machine learning models, AI-enabled automation, and advanced operations research algorithms allows us to optimize over trillions of possible routes in near real time.

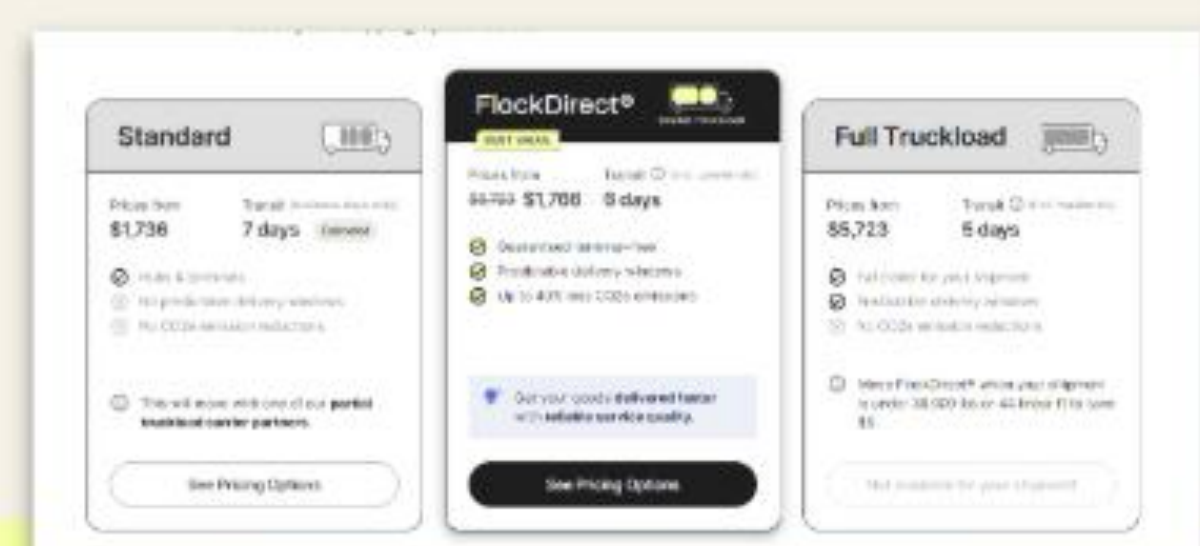
CHALLENGE

We have to provide prices to the shipper **before we know how the shipment will move** (e.g. in what shared truckload, or solo)

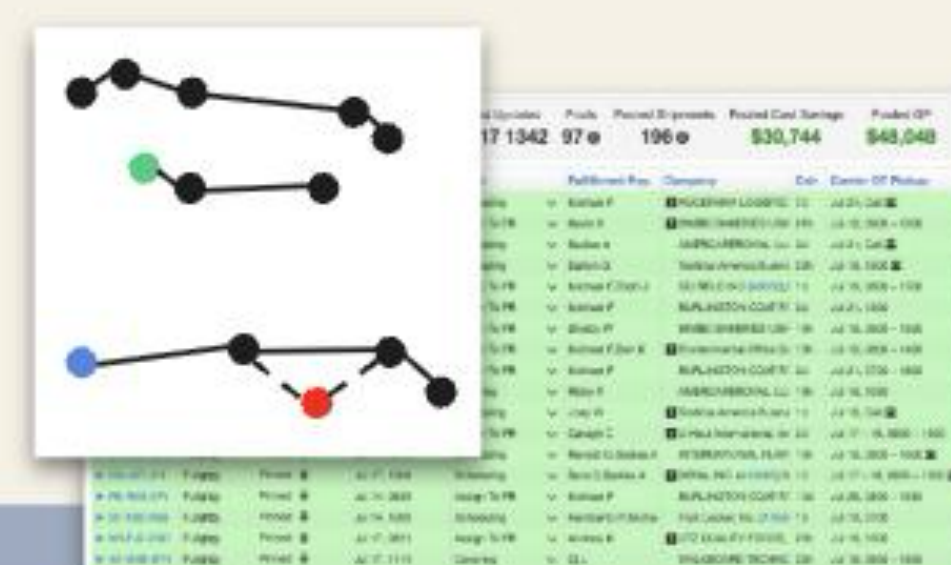
Prioritizing and executing STL pools incurs **significant operational complexity** and navigating tradeoffs that change in **minutes, not days**

There is **no external market benchmark** for STL pools, and therefore significant **variance in what carriers evaluate as a fair rate**

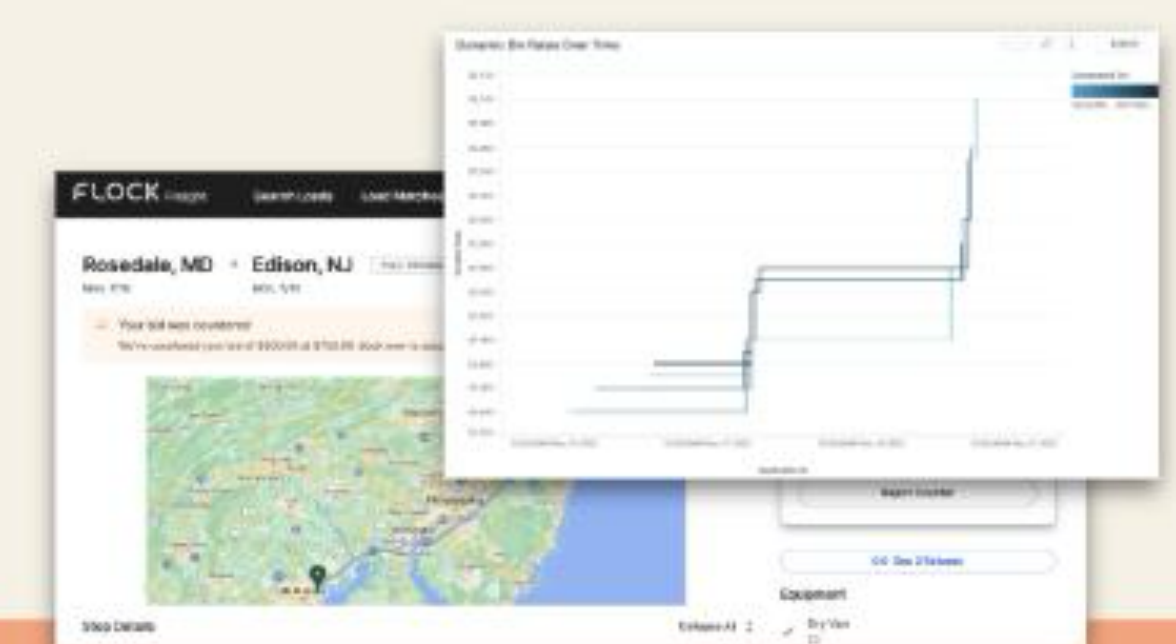
LIFECYCLE OF A SHIPMENT



Quote



Order



Fulfill

SOLUTION

Flock prices in the portfolio risk, and uses an ensemble of models to predict counterfactual cost outcomes and probabilities to arrive at an estimated cost basis. This allows us to **provide a simplified, up front price** that is not contingent on how we ultimately end up moving the shipment

Our optimization systems explicitly **model end-to-end execution risk**, balancing raw cost efficiency with the likelihood of realizing those gains. Optimization inputs are constantly updated as shipments are covered, offers come in, etc. to produce an updated fulfillment plan **every ~2-3 minutes**.

When a shared truckload opportunity is identified, **we forecast its offer distribution** to ground negotiations. We simultaneously evaluate the **likelihood that a particular carrier will make a competitive offer** for use in search relevance and carrier outreach.

FIGURE 1: THE KEY CHALLENGES IN BRINGING STL TO MARKET AND HOW FLOCK ADDRESSES THEM, ORGANIZED BY MILESTONES IN THE LIFECYCLE OF A SHIPMENT

IIa. Pricing Before Knowing How the Freight Will Move



Let's start with quoting. In every STL pool, one of the constituent shipments is quoted and ordered first, before all the others. At that point in time, an STL provider like Flock doesn't know how it will be fulfilled because the other shipments it will eventually ride with have not yet been ordered. It could move in a 75% full STL pool, in a highly optimized 95% full STL pool, or even as an individual shipment if there weren't any others that were a good match. At the same time, shippers need timely and durable rates that won't change depending on how the shipment ultimately ends up moving.

In order to meet these expectations while providing as competitive rates as possible, Flock's technology computes the likelihood of key fulfillment outcomes at quote time based on factors like the shipment's size, weight, origin, destination, and pickup and delivery flexibility to be able to provide a risk-adjusted price to our shippers that we can honor even if we end up deciding not to pool that particular shipment. Using this probabilistic pricing technique allows Flock to accurately predict and responsibly manage its costs across its entire portfolio.

IIb. The Vehicle Routing Problem



At its core, Flock is solving a combinatorial optimization problem over its network of shipments which is an advanced variant of what researchers call the Vehicle Routing Problem (or more specific to our context, a Multi-Dimensional, Capacitated Pickup and Delivery Problem with Time Windows and Last In, First Out Loading). What makes the problem hard is scale.



As a toy example, with just 500 shipments in the network, there's $\sim 10^{1333}$ possible STL pool routes to choose from. If we reasonably constrain our attention to just routes containing 5 shipments or fewer, there's still ~ 10 trillion possibilities to explore and choose from. Some of those routes can be quickly ruled out (e.g. pooling an LA $\rightarrow$ DAL shipment with a DAL $\rightarrow$ LA shipment), and so academics have spent decades devising clever ways to solve these problems without having to go through all of those possibilities using algorithms called metaheuristics (Figure 2).

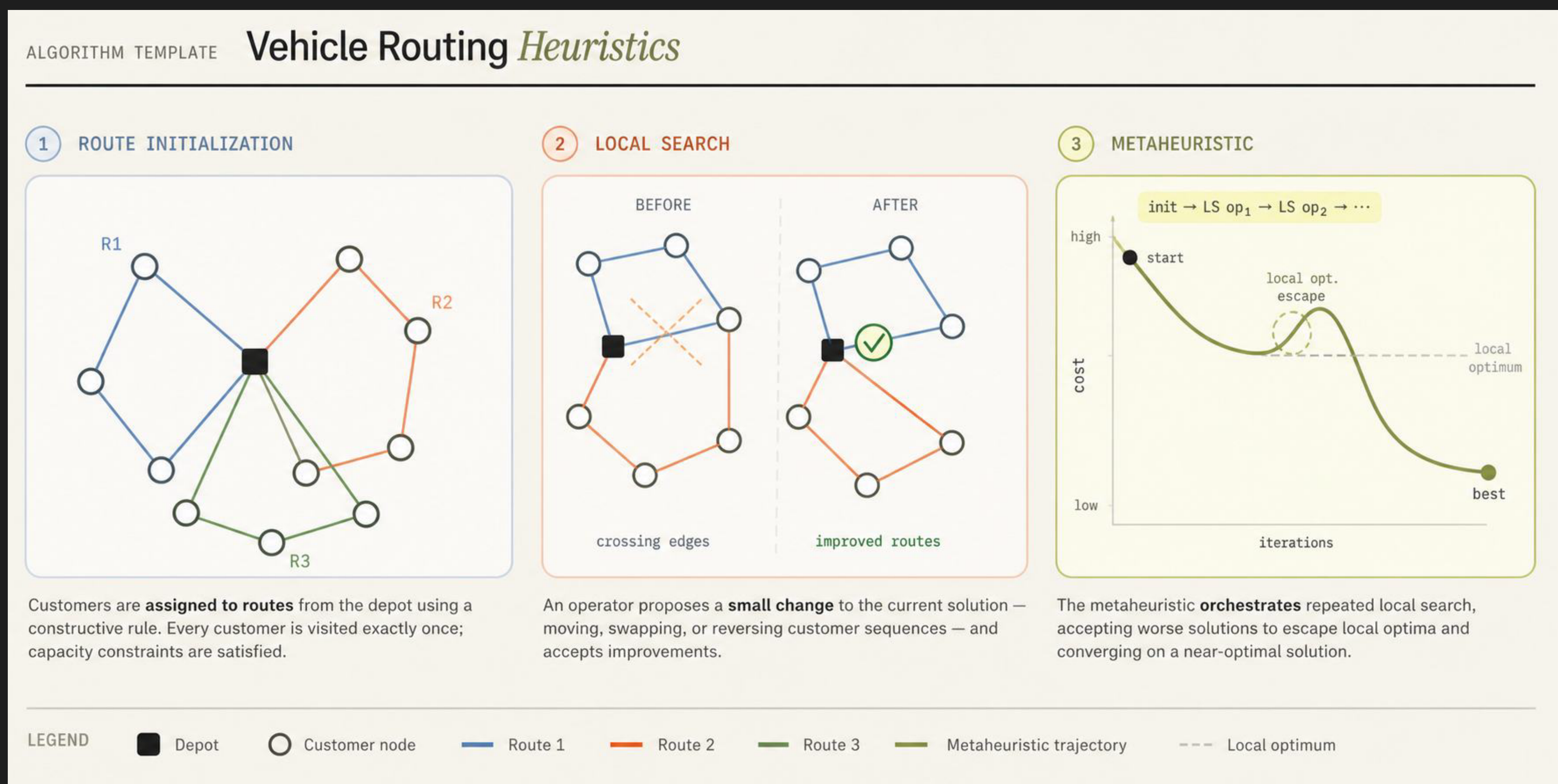


FIGURE 2: AN ALGORITHMIC SKETCH OF HOW INDUSTRIAL GRADE SOLVERS WORK TO SOLVE VEHICLE ROUTING PROBLEMS.

Generally, these algorithms can take hours to run, and are intended to solve a static problem (e.g. input tomorrow's data, solve once, and execute the plan). However, Flock's ensemble of solvers run and adapt in minutes, allowing it to incorporate feedback and new information in near real time as shipments get ordered, picked up, and details like appointments or shipment details get modified throughout the day.

IIc. Time as a Resource



In a traditional freight setting, it's advantageous to find carriers and book loads as fast as you can. Carriers are willing to offer more competitive rates in exchange for the convenience and security of knowing the plan in advance. For an STL provider, time becomes a resource that has to be managed - book too early, and you'll be unable to take advantage of pooling opportunities that become available in the future; book too late, and carriers will charge a premium for the short notice. A similar tradeoff exists when it comes to appointment coordination. Setting appointments quickly can be important to a good shipper experience. However, setting appointments too early can make otherwise efficient STL pools infeasible.

To navigate these complexities, Flock's technology forecasts and updates how fulfillment and execution decisions made at the individual shipment level are expected to impact its future outcomes. We then leverage those predictions to influence how our carrier sales team operates and brings STL to market.

IIId. Optimizing in the Real World



It's clear that the STL mode depends on an ability to create more efficient outcomes than the status quo, but an elegant, highly efficient plan on paper is only as valuable as the ability to execute on it. An STL pool with 10 distinct pickup locations, and 10 distinct dropoff locations all of which have strict receiver requirements and which leaves no timing slack for unexpected traffic may be a highly efficient use of a carrier's vehicle, but it will very likely fail in practice.

Flock is able to leverage its years of data executing STL pools to predict the end-to-end risk of fulfilling each candidate STL pool, including (but not limited to) the ability to source capacity in a timely manner, the possibility of participating shipments not being ready on time or with misreported details, etc. We then use these predictions to optimize for the actual delivered efficiencies we're able to create.

III. The Power of the Network



The power of STL and its ability to improve outcomes increases the more freight there is available to ride together. In general terms, the number of viable STL pooling opportunities increases exponentially the more shipments there are in the network. This is helpful both to create more efficient plans in the first place, but also to create more resilient and consistent outcomes. The reason is similar to that of the famous birthday paradox, where you only need 23 people for it to be likely that two of them share a birthday. Every additional shipment added to an STL network has a chance to be a good complementary partner for every other shipment already in the network, compounding the impact of the incremental volume. Empirically, this is exactly what we observe: as Flock has grown its volume, the rate at which shipments move in STL pools increases (Figure 3).

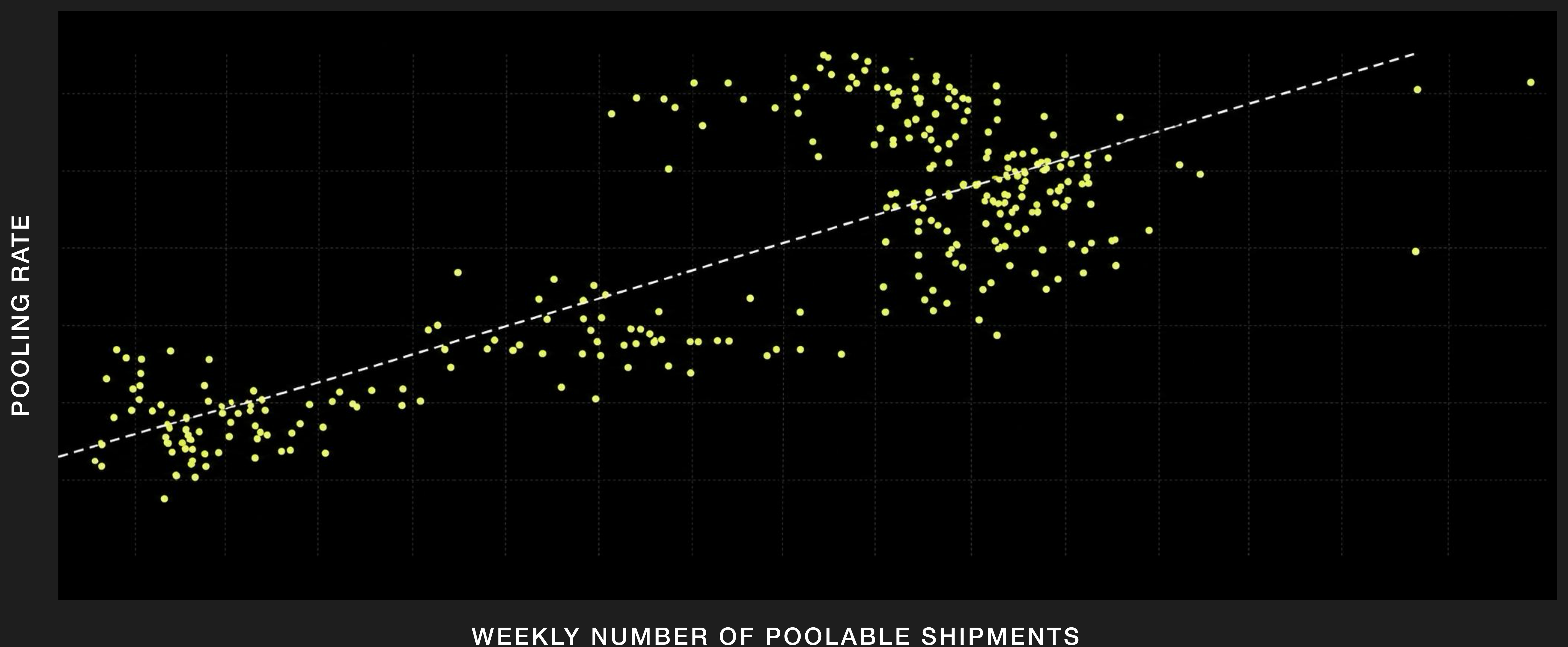
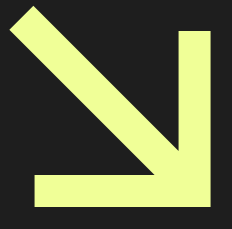


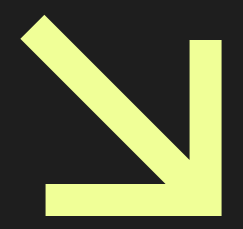
FIGURE 3: A PLOT OF POOLING RATE (Y-AXIS) AS A FUNCTION OF WEEKLY NUMBER OF POOLABLE SHIPMENTS (X-AXIS) DEMONSTRATING THE STRONG EFFECTS OF NETWORK DENSITY ON POOLING SUCCESS



In fact, a larger network not only increases the rate at which shipments move in STL pools, it also increases the quality of those pools. A larger network increases the likelihood that a shipment will move in an STL pool that:

- ✓ Fills the trailer
- ✓ Shares nearby pickups and dropoffs
- ✓ Requires the carrier to drive minimal additional mileage relative to the individual constituent shipments
- ✓ Keeps the carrier moving (e.g. not waiting for an intermediate stop to accept them)

This is a well studied phenomenon in the ridesharing research literature, both theoretically ([Santi et al.](#), [Tachet et al.](#)), and empirically in case studies of cities like Chicago and Toronto ([Liu et al.](#), [Young et al.](#)) that as network density and size grow, match rate increases and detour length decreases.



Moving more shipments more efficiently in high quality STL pools is also what allows Flock to offer more competitive rates to both shippers and carriers. When a shipment moves in one of those STL pools, it lowers the per shipment cost to move it, while still being able to offer above FTL rates to carriers to haul the STL pool. Those lower fulfillment costs are then recognized by our pricing technology and extended back to shippers in the form of lower prices. In this way, all shippers and carriers in an STL network cooperate to create better outcomes for everyone (Figure 4). If that sounds aspirational, it's not: the vast majority of STL pools we execute involve multiple shippers' shipments.

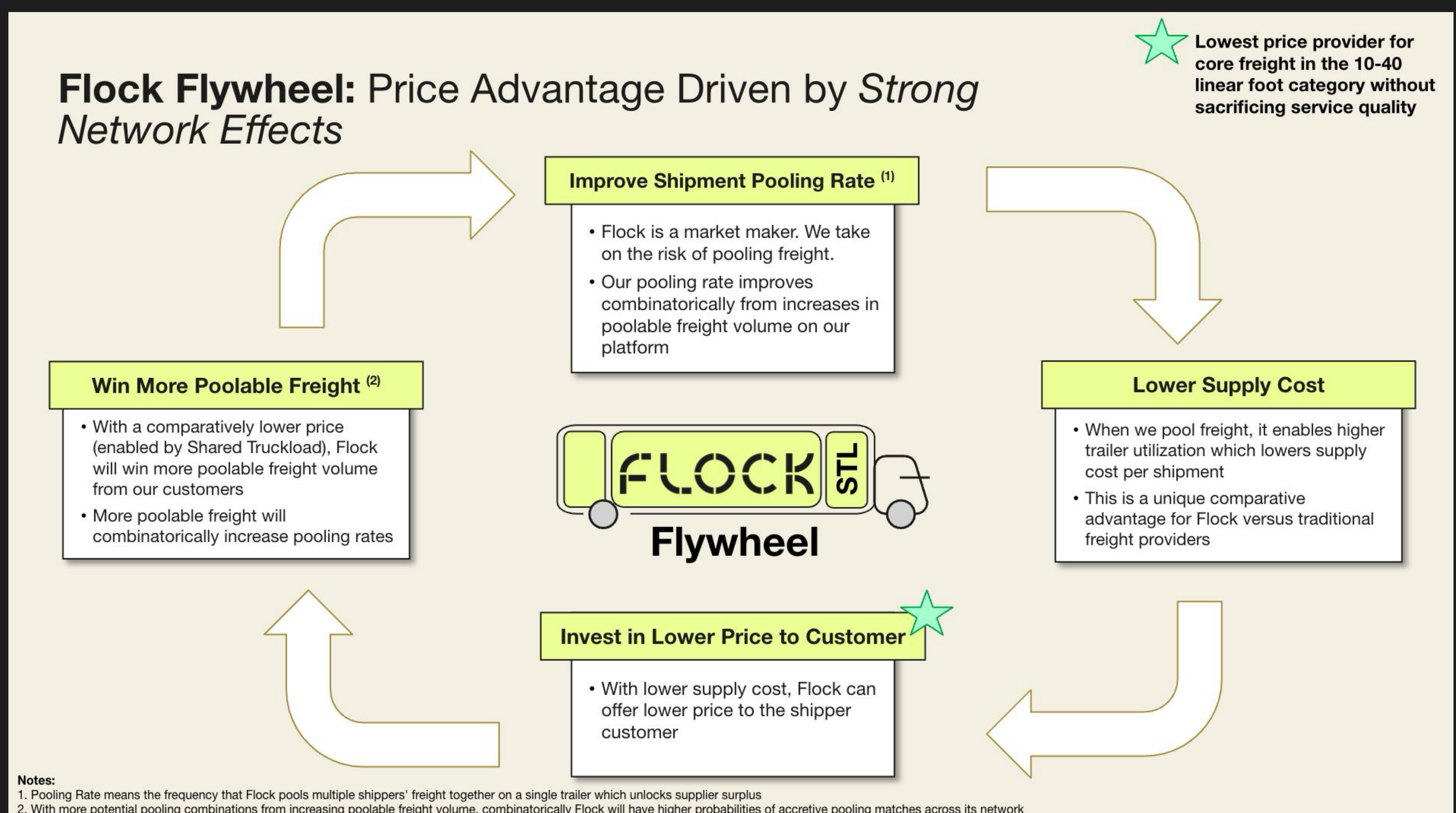


FIGURE 4: THE FLOCK FLYWHEEL, ILLUSTRATING HOW BETTER POOLING OUTCOMES RESULT IN SHARED SUCCESS FOR ALL PARTICIPATING SHIPPERS AND CARRIERS

IV. How to Get the Most Out of STL



Now that we've outlined some of the intricacies involved with executing STL pools, and established that shippers are active participants in creating better outcomes for themselves and others, we'll briefly discuss some concrete steps they can take to maximize their ability to get value out of an STL network:

- ✓ **Minimize Filtering:** As discussed in the last section, STL works better with more freight. In practice, we've seen enterprise shippers attempt to create their own multi-stops, and think of an STL provider only as helping with the 'leftovers.' Even with mature, large scale shippers we often identify STL pools that improve upon a shipper's own multi-stops because we have a larger set of denser volume to match across all of our shippers. By sending all eligible freight to an STL provider, shippers can achieve more optimal outcomes when compared to creating multi-stops within a shippers' own network only.
- ✓ **Maximize Lead Time:** The more lead time a shipper can provide, the greater the likelihood that their shipments will be fulfilled in an STL pool.
- ✓ **Maximize Flexibility:** Work with your STL provider to maximize the available pickup and delivery times for your shipments and facilities - whether that's through managing to must-arrive-by dates to create pickup flexibility or making sure to periodically audit whether a facility needs appointments or allows appointment windows. Time-related constraints are the largest and most common blocker to maximizing STL outcomes.
- ✓ **Streamline Scheduling Operations:** The easier and faster it is for your STL provider to schedule appointments and get visibility into available appointment times (ideally automatically via API or portal), the greater the likelihood that shipments will be fulfilled in an STL pool.

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