

Using Optimisation and Genetic Algorithms to Inform Logistics Decisions

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Paul Derbyshire
Senior Technical Advisor
BearingPoint

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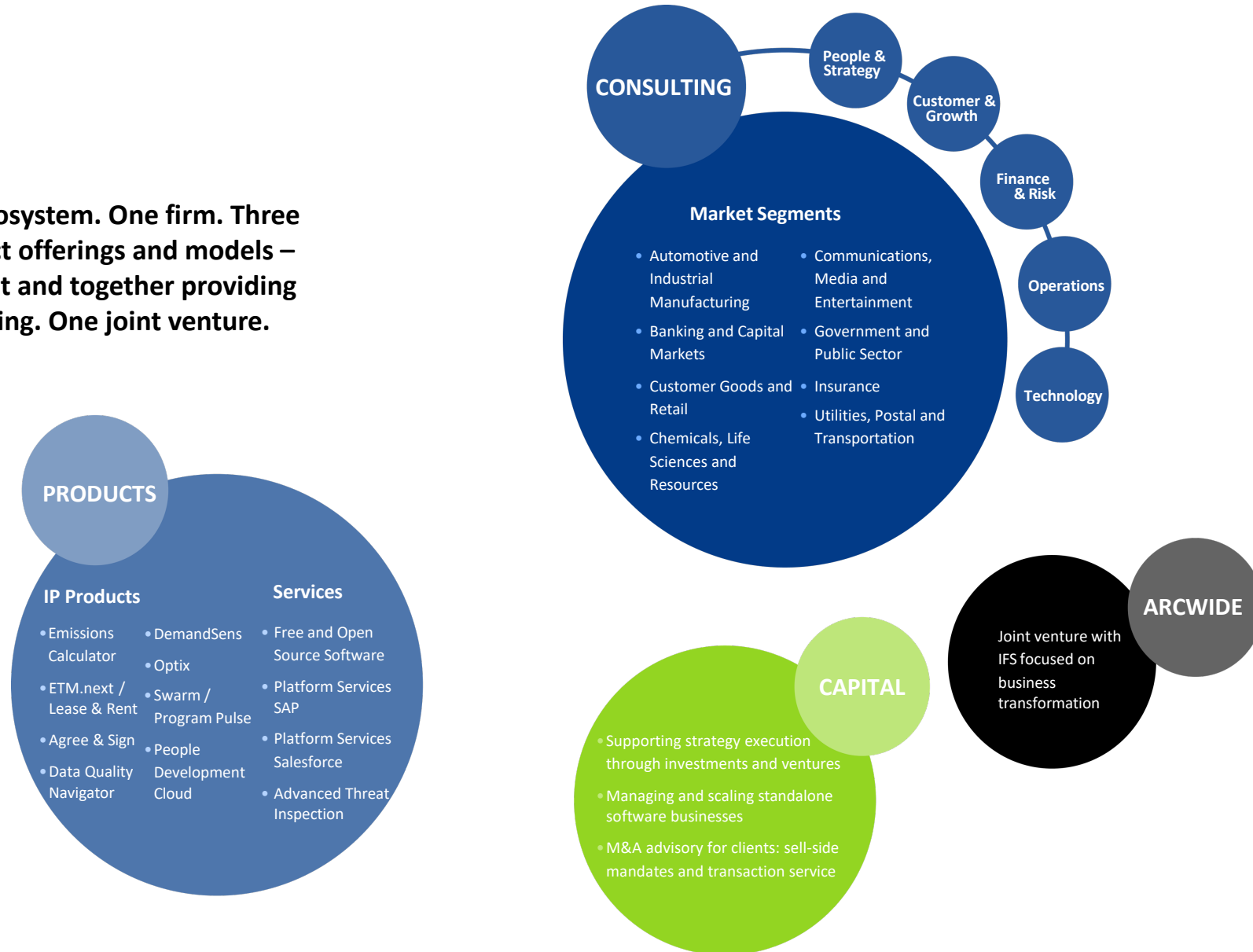
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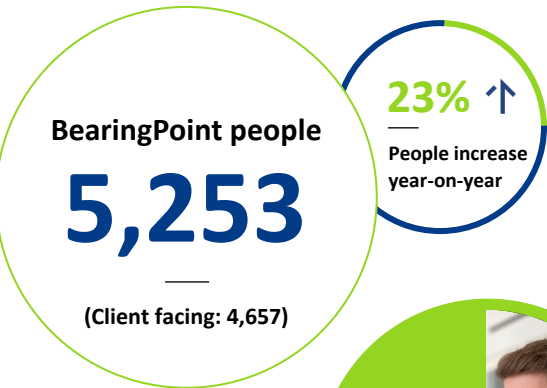
A story of **unity**

The unique BearingPoint ecosystem. One firm. Three business units – with distinct offerings and models – focused on their own market and together providing technology-enabled consulting. One joint venture.



Our year in numbers

Numbers only tell part of a story, but they show how far we've come. In 2022, we exceeded our own predictions and grew stronger with every step.



The Challenge

What were we being asked to solve?



Setting the scene



A major **grocery** and **general merchandise** retailer



Significant **growth**



Multiple product types and **temperature regimes** across the product portfolio

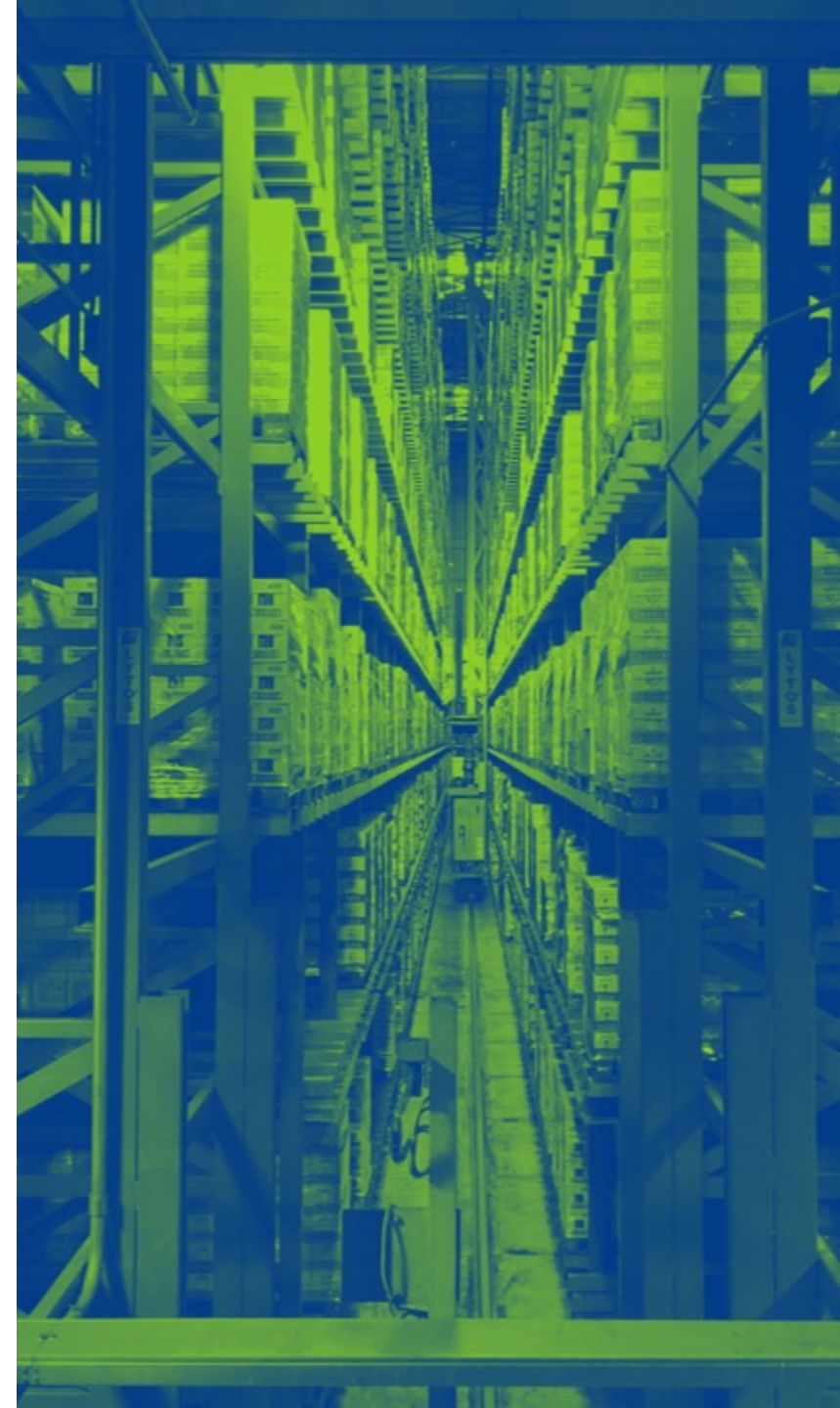
- Manually Handled & Automation Handled Products
- Chill / Fresh
- Frozen
- Ambient
- Temperature sensitive



Designing a **new automated DC** to service stores and provide elements of **hub distribution**



Serving **hundreds of stores**



The Challenge:

Create a schedule that meets store service requirements with optimised fleet and automation usage

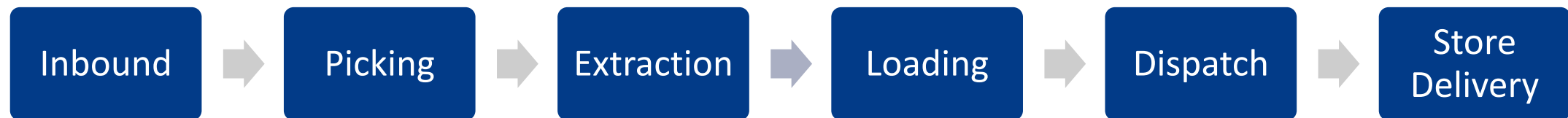
Create a schedule that meets store service requirements, optimises fleet and maximises use of automation

Optimising across multiple related functions

Create a cost optimised schedule for key activities for peak and average days. Taking into consideration:

- Order release times
- Store delivery windows and volumes
- Trailer parking and electric hook-up
- Unloading / loading bay capacities
- Fleet size and mix
- Storage capacity
- Automation capacities
- Drive times
- Shift labour
- Delivery and vehicle costs
- Labour costs

Key activities for scheduling

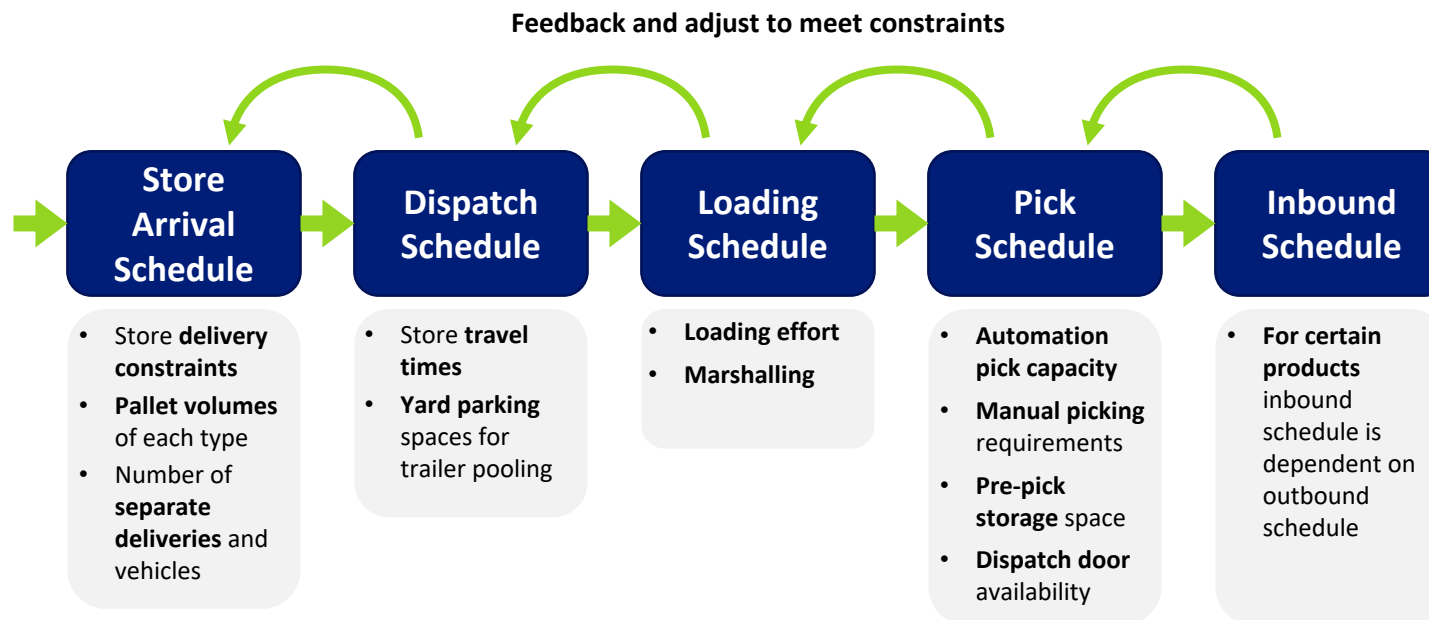


In order to be effective and to maximise the return on the investment in automation the whole site needs to operate as a single, inter-linked, holistic entity (akin to a manufacturing production plant)

The size and complexity of the challenge

Creating a feasible schedule within the constraints of the site design is highly complex

- There are many **competing factors to consider and test at the same time**
- Each “decision” **impacts processes and capacities before and after**
- There may be a **number of possible solutions**



- **Hundreds of stores**
- **Multiple store delivery slots**
- **8 product types**
- **Fleet size and mix**
- **Site constraints**
- **Time granularity of 15 mins**





There could be 10 million+ variables in this problem

Exploring Our Options

What options did we look at?

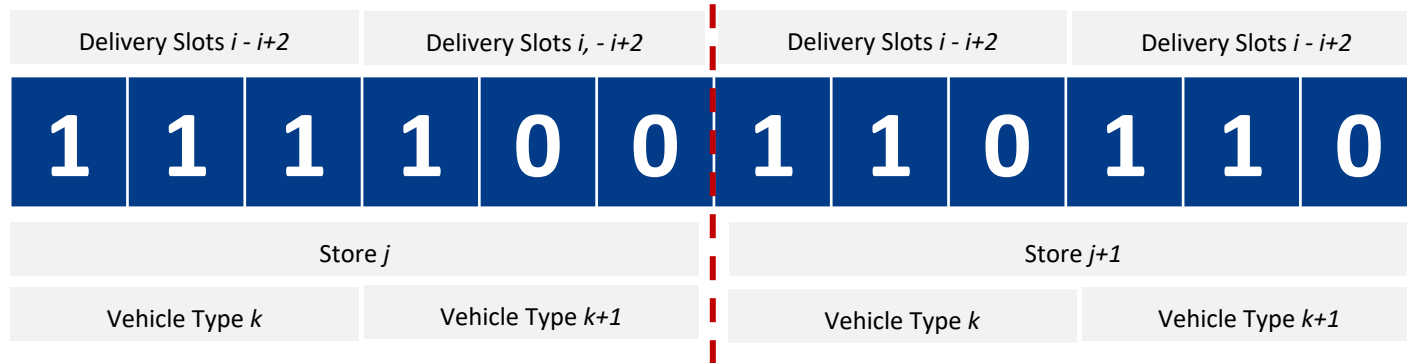


What approaches did we consider?

		The Good	The Less Good
	Single MIP Optimisation model	<ul style="list-style-type: none"> • Deals with everything in a single MIP model. Conceptually more straightforward • Does not require additional functions to assemble sub models 	<ul style="list-style-type: none"> • The size of the problem! The number of variables and constraints, based on previous examples of MIPs we'd run for similar logistics models
	A heuristic backward-scheduling model	<ul style="list-style-type: none"> • Potentially quicker to build, easier to build in specific rules of thumb • Would require some level of simplification 	<ul style="list-style-type: none"> • How do we choose the first delivery schedule and vehicle type? • The number of variables and rules would still be significant to manage
	A backward-scheduling model inside a harness	<ul style="list-style-type: none"> • Allows us to evaluate multiple delivery schedules and vehicle types as starting points for the backward schedule 	<ul style="list-style-type: none"> • Which type of harness? Genetic Algorithm? Reinforcement Learning?
	A backward-scheduling model inside a Genetic Algorithm harness	<ul style="list-style-type: none"> • Allows us to parallelise the optimisation of multiple delivery schedules • Ease of use 	<ul style="list-style-type: none"> • Convergence can be slow due to chromosome length

Using a chromosome to represent a schedule

A chromosome made up of multiple genes



Each gene in the chromosome codifies



Delivery time



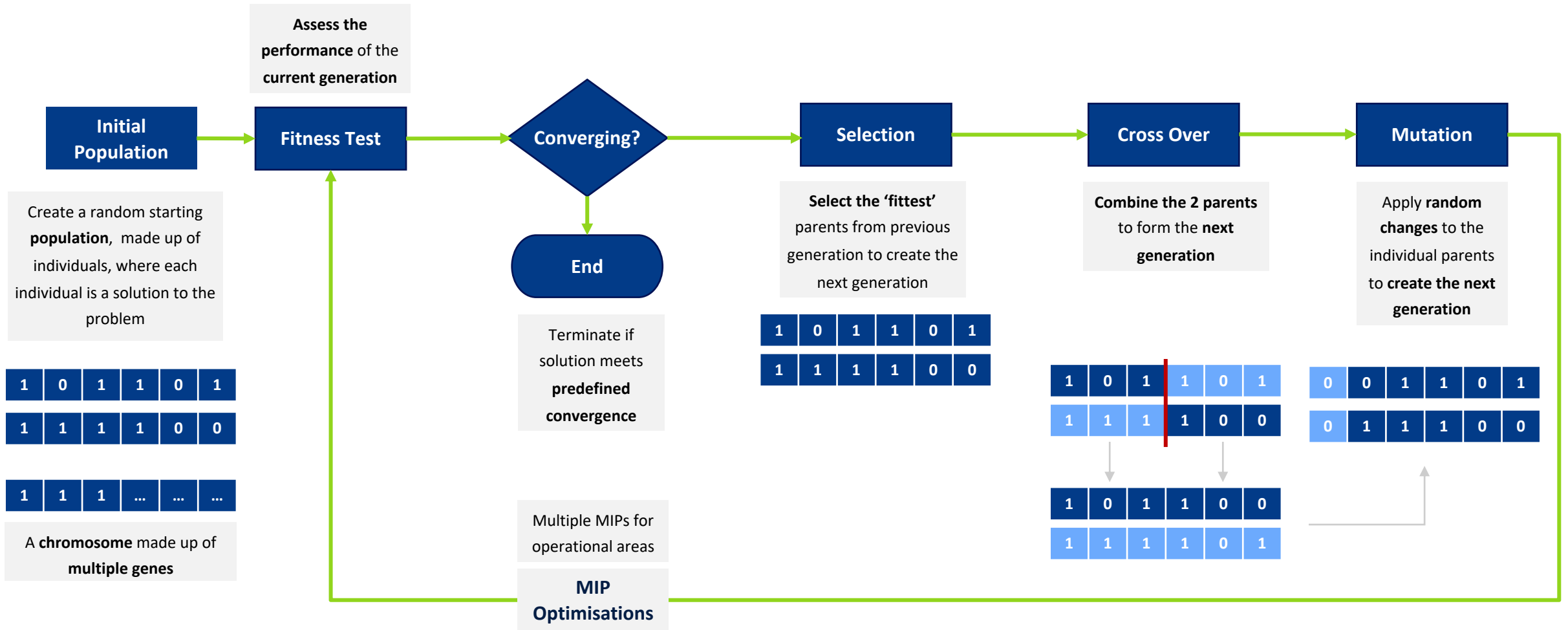
Store number



Vehicle type

An alternative approach using genetic algorithms

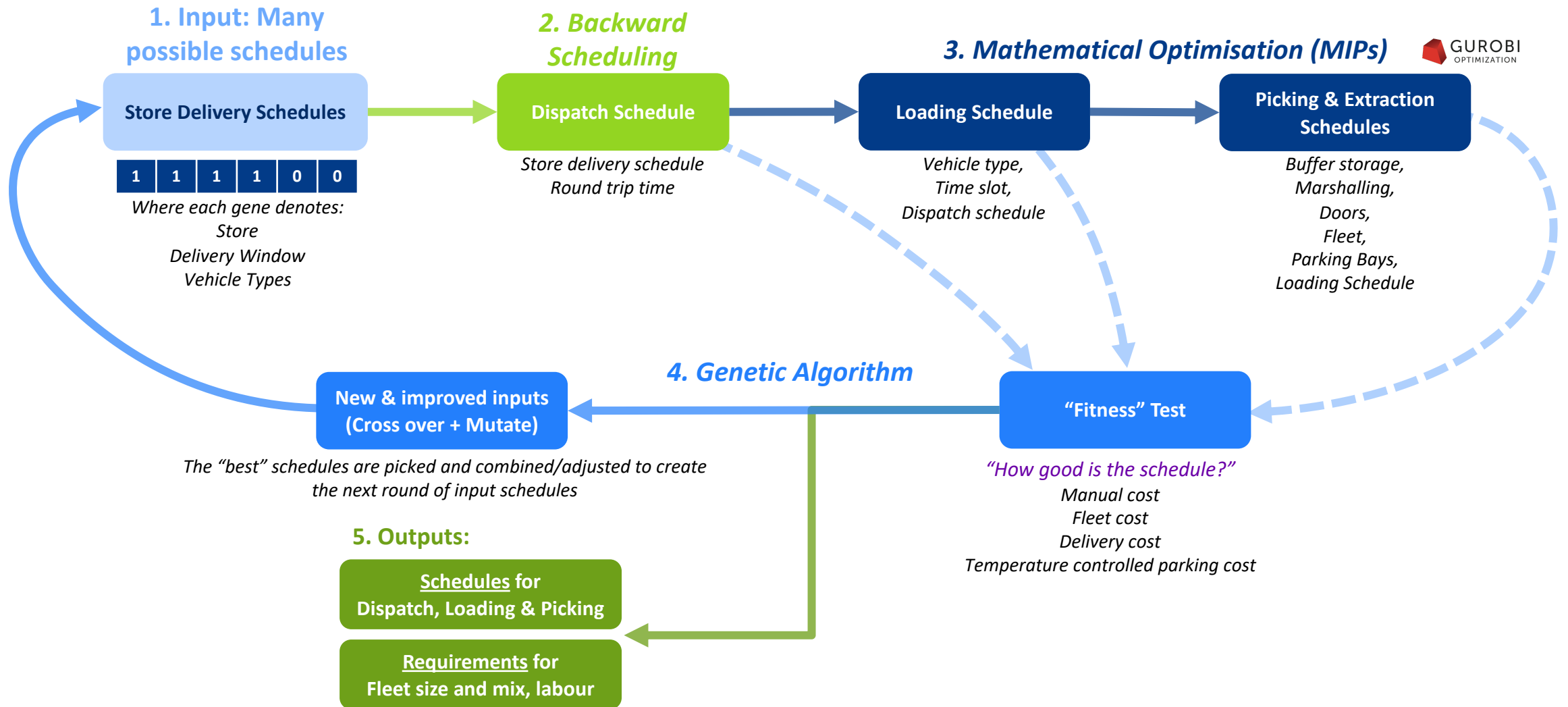
Using nature's way to evolve to the best solution



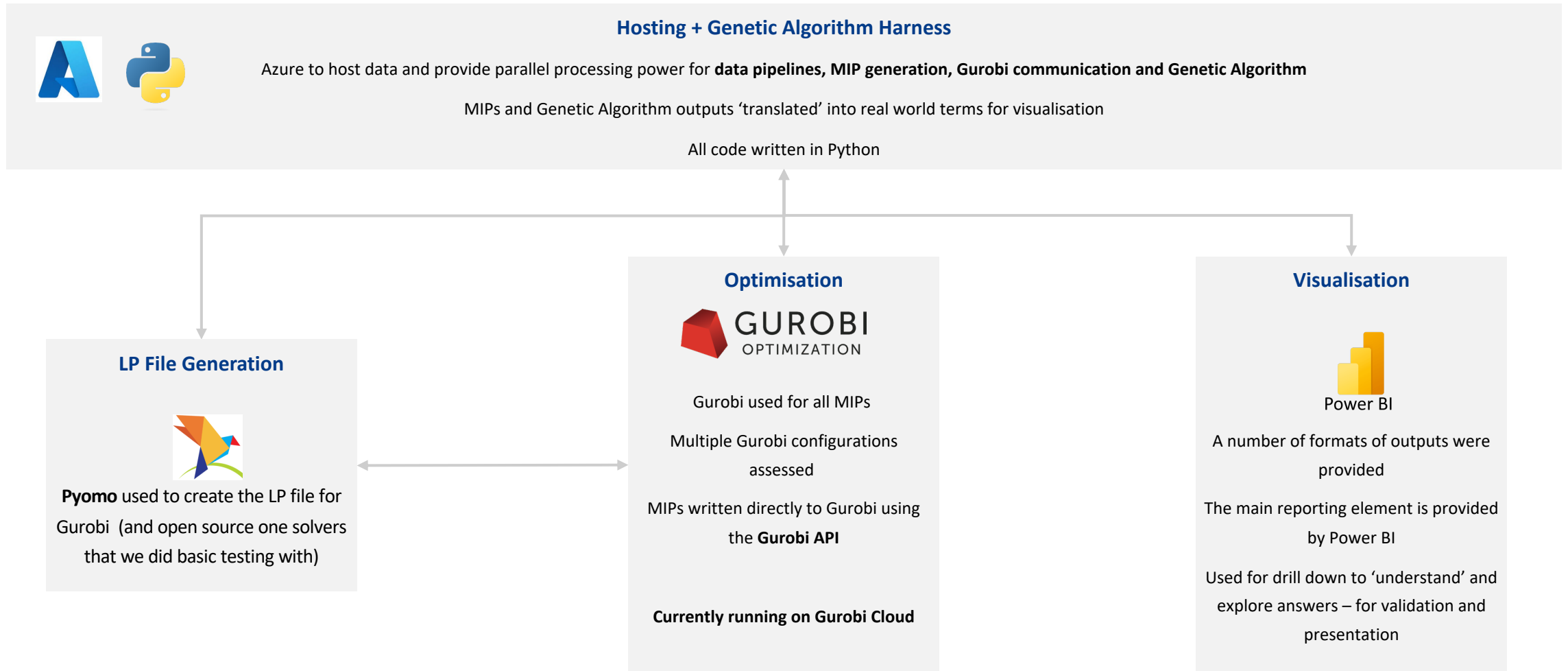
A person's hands are shown holding a glowing lightbulb. The lightbulb is illuminated from within, casting a warm glow. The background is a solid blue color. The text "Crafting the Solution" is overlaid on the left side of the image.

Crafting the Solution

What did this look like for us?



Infrastructure used



Some key facts

Chromosome length

16k-64k



Chromosome population

96

Generations Run

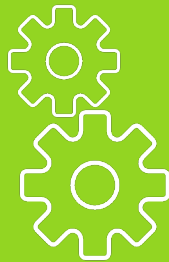
**Up to
20**



... before costs convergence

MIPs used per Chromosome

5-14



To cover functional
areas and product
types

Speed



**Up to 33 MIPs
per minute**

16 Chromosomes in parallel

MIP binary variables

~800k

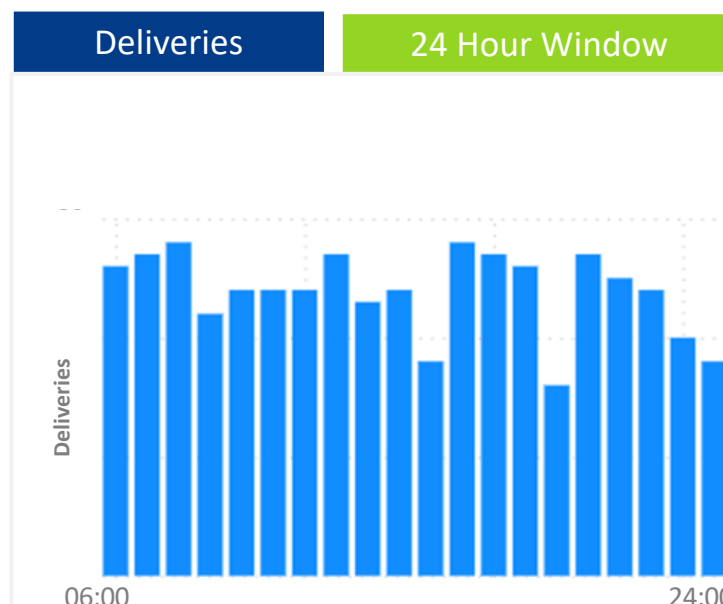
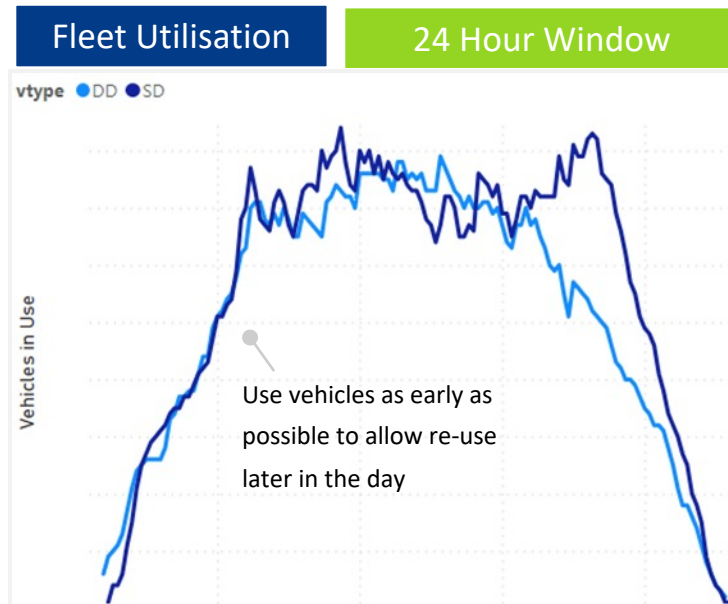
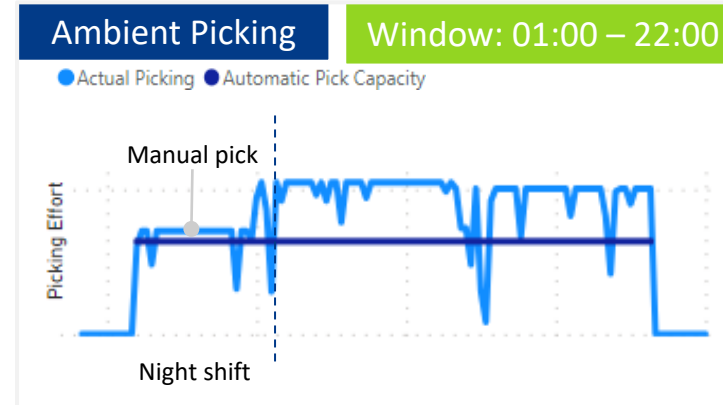
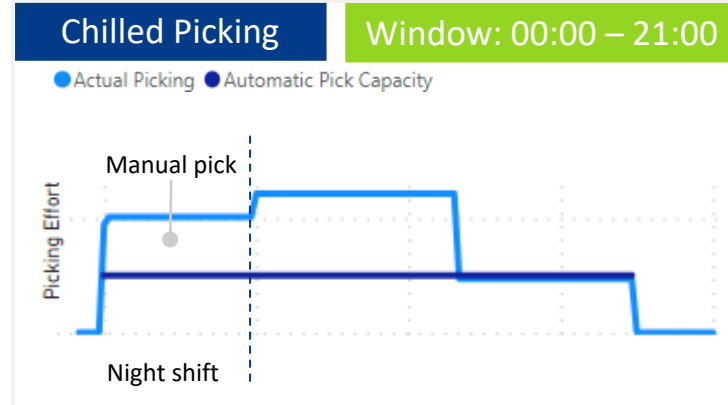


MIP constraints

~30k

Sample scenario modelling

Scenario Outputs



Key Outputs

- Optimal timings for each activity required to get all orders to stores
- The number of colleagues required on each shift to complete work
- Optimal delivery vehicle type mix and number required
- Identified potential future peak day bottleneck areas
- Clear indication of how store delivery timings impact DC activity and DC labour requirements

A person is sitting on a rocky ledge, looking out over a vast sea of clouds. The scene is captured in a high-angle shot, with the person's silhouette in the foreground. The clouds are dense and stretch far into the distance, creating a sense of depth and scale. The sky is a clear, bright blue, and the overall atmosphere is serene and contemplative.

Key Takeaways

Lessons learned



Optimising the **end-to-end** operation in small time periods is **complex**



Genetic algorithms are a great way to **parallelise an optimisation(s)**



A single **complex MIP** can be **traded for multiple MIPs** with a Genetic Algorithm but at the **cost of convergence** time



Iterative building and testing worked well. **Start with shorter chromosomes and build up from there**



There's always a way to get to the answer!



Key takeaways

3 key themes



Genetic Algorithms

Are a great approach to solving large scale problems. Combining with MIP can speed up the evolution



Break the problem down

Assess ways in which functional areas can be optimised and combined



Parallel running

Make use of the parallel run capability afforded by Genetic Algorithms



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