Approximate Dynamic Programming Captures Fleet Operations for Schneider National

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Outline

- The operational problem
- Modeling and optimization
- Algorithmic challenges
  - Aggregation
  - Stepsizes
  - Pattern matching
- Calibration and validation
- Policy studies
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- The operational problem
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- One of the largest truckload carriers in the U.S.
- Manages fleet of over 15,000 drivers
The operational problem

The one-way service network

» 6,500 drivers
  • National and regional
  • Independent owner-operators and company employees
  • Solos and teams

» 50,000 loads moved over 4 week period
  • Regional and transcontinental
  • Domestic and Canadian

» Schneider must balance:
  • Empty miles
  • Customer service
  • Getting drivers home
  • Driver regulations
• Effect of changes in driver regulations
• Policies for driver domiciling/hiring
• Policies for getting drivers home
• Changes in rules for handling Canadian drivers
• Impact of changes in policies for pickup and delivery appointments
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Modeling and optimization

1980’s – Single commodity network flow
Modeling and optimization

1990’s – Multicommodity network flow

How do we make this *stochastic*?
Modeling and optimization

- **Modeling drivers:**
  - Type
  - Domicile
  - Current location
  - Next available time
  - Time away from home
  - Next scheduled (or desired) time at home
  - DOT road hours
  - DOT duty hours
  - On-duty hours over last eight days

- **And loads:**
  - Origin
  - Destination
  - Ready date/time
  - Appointment data
  - Priority flags
  - Revenue

\[
D_{tb} = \text{Number of loads with attribute } b
\]

\[
R_{ta} = \text{Number of drivers with attribute } a
\]
Modeling and optimization

The state variable:

\[
R_{ta} = \text{Number of drivers with attribute } a.
\]

\[
R_t = (R_{ta})_{a \in A} = \text{Driver state vector}
\]

\[
D_t = (D_{tb})_{b \in B} = \text{Load state vector}
\]

\[
S_t = (R_t, D_t) = \text{System state vector}
\]

“really big vectors!”
Modeling and optimization

Optimizing over time

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Modeling and optimization

- We can formulate the problem as a dynamic program:

  \[ V_t(S_t) = \max_x \left( C_t(S_t, x_t) + E\{V_{t+1}(S_{t+1}) \mid S_t\} \right) \]

  where \( S_{t+1} = S^M(S_t, x_t, W_{t+1}) \)

  - The curses of dimensionality
    - State space
    - Outcome space
    - Decision space

  - The computational challenge:
    - How do we find \( V_{t+1}(S_{t+1}) \)?
    - How do we compute the expectation?
    - How do we find the optimal solution?
Modeling and optimization

- Algorithmic strategy using approximate dynamic programming:

  1) Eliminate the expectation using the concept of the *post-decision state variable*

  2) Replace the value function with an approximation

  3) Design an efficient strategy for learning the value of being in a very high-dimensional state
Pre- and post-decision states

The pre-decision state: drivers and loads

\[ S_t = (R_t, D_t) \]
Pre- and post-decision states

The post-decision state - drivers and loads after a decision is made:

\[ S_t^x = S_{t,M,x}^x(S_t, x_t) \]
Pre- and post-decision states

The transition: Adding new information

\[ S_t = S_t^{M,W}(S_t^x, W_{t+1}) \]

\[ W_{t+1} = (\hat{R}_{t+1}, \hat{D}_{t+1}) \]
Pre- and post-decision states

- The next pre-decision state

\[ S_{t+1} \]
We use the post-decision state to break Bellman’s equation into two steps

» A deterministic optimization problem

\[ V_t(S_t) = \max_x \left( C_t(S_t, x_t) + V_t^x \left( S_t^x(S_t, x_t) \right) \right) \]

• We can solve this using commercial solvers such as CPLEX

» An expectation

\[ V_t^x(S_t^x) = E \left\{ V_{t+1}(S_{t+1}) \mid S_t^x \right\} \]

• We will approximate this using statistical and/or machine learning techniques
Solving the deterministic optimization problem:

» We replace the value function in

\[
V_t(S_t) = \max_x \left( C_t(S_t, x_t) + V_t^x \left( S_t^x(S_t, x_t) \right) \right)
\]

» … with an approximation. For this application, we were able to use:

\[
V_t(S_t^x) \approx \tilde{V}_t(R_t^x) = \sum_{a \in A} \tilde{v}_{ta} \cdot R_{ta}^x
\]
Approximate dynamic programming

Step 1: Start with a pre-decision state $S_t^n$

Step 2: Solve the deterministic optimization using an approximate value function:
$$\max_x \left( C_t(S_t^n, x_t) + V_t^{n-1}(S_t^n, x_t) \right)$$
to obtain $x_t^n$ and marginal values $\hat{v}_a^n$.

Step 3: Update the value function approximation
$$\bar{v}_a^n = (1 - \alpha_{n-1})\bar{v}_a^{n-1} + \alpha_{n-1}\hat{v}_a^n$$

Step 4: Obtain Monte Carlo sample of $W_t(\omega^n)$ and compute the next pre-decision state:
$$S_{t+1}^n = S_t^M(S_t^n, x_t^n, W_{t+1}(\omega^n))$$

Step 5: Return to step 1.

Deterministic optimization
Statistical learning
Simulation
Modeling and optimization
Modeling and optimization
Modeling and optimization
Modeling and optimization
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Approximating the value function

Our optimization problem at time $t$ looks like:

$$V_t(S_t) = \max_x \left( C_t(S_t, x_t) + \sum_{a \in A} \bar{v}_{ta} \cdot R_{ta}^x \right)$$

There are a lot of these attributes!

» For this project, we had to develop novel machine learning strategies to estimate this function.
Approximating the value function

Different levels of aggregation:

\[
a = \begin{bmatrix}
\text{Time} \\
\text{Region Location} \\
\text{Region Domicile} \\
\text{Type}
\end{bmatrix}
\begin{bmatrix}
\text{Time} \\
\text{Region Location} \\
\text{Type}
\end{bmatrix}
\begin{bmatrix}
\text{Time} \\
\text{Region Location} \\
\text{Area Location}
\end{bmatrix}
\]

\[|A| \approx 3,293,136 \quad 33,264 \quad 5,544 \quad 672\]
Approximating the value function

Adaptive hierarchical estimation procedure developed as part of this project (George, Powell and Kulkarni, 2008)

» Use weighted sum across different levels of aggregation.

$$\bar{v}_a = \sum_g w^{(g)}_a \bar{v}^{(g)}_a$$

where

$$w^{(g)}_a \propto \left( Var \left( \bar{v}^{(g)}_a \right) + \left( \beta^{(g)}_a \right)^2 \right)^{-1}$$

Both can be computed using simple recursive formulas.


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Approximating the value function

Average weight on most disaggregate level

Average weight on most aggregate levels

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Slide 30
Approximating the value function
Approximating the value function

- **Weighted Combination**
- **Aggregate**
- **Disaggregate**
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Stepsizes

The role of stepsizes in the value function updating equation:

\[ \overline{v}_{a}^{n} = (1 - \alpha_{n-1})\overline{v}_{a}^{n-1} + \alpha_{n-1}\hat{v}_{a}^{n} \]

- Updated estimate
- Old estimate
- New observation

The stepsize
“Learning rate”
“Smoothing factor”
Stepsizes

Even stepsizes which are proven to converge to optimality in the limit can work extremely badly

Smoothed estimate using $1/n$
Stepsizes

- New optimal stepsize formula developed as part of this research:

\[
\alpha_n = 1 - \frac{(\sigma^2)^n}{(1 + \lambda^{n-1})(\sigma^2)^n + (\beta^n)}
\]

where:

\[
\lambda^n = (1 - \alpha_n)^2 \lambda^{n-1} + (\alpha_n)^2
\]

As \((\sigma^2)^n\) increases, stepsize decreases toward 1/n

As \(\beta^n\) increases, stepsize increases toward 1

Stepsizes

The new optimal stepsize formula produced
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Pattern matching

- There are certain corporate behaviors that are difficult to match with engineering rules:
  - At Schneider, drivers working in teams have to be assigned to longer loads, on average
  - Drivers that own their equipment have the second-longest average length of haul
  - Single drivers using company-owned equipment move loads which, on average, are the shortest

Pattern matching offers a viable alternative to incorporate these behaviors into the model
Pattern matching

- The engineering approach

\[
\max_x \left( E \left\{ \sum_t \gamma^t C_t(S_t, x_i) \mid S_0 \right\} \right)
\]

- We add in a *pattern metric* that penalizes deviations from the historical pattern of the distribution of length of haul for each driver type

\[
\max_x \left( E \{ C(S, x) \} - \theta \ast H(x, \rho) \right)
\]

The difference between the model solution and historical patterns.
Pattern matching

- The engineering approach

\[
\max_x \left( E \left\{ \sum_t \gamma^t C_t(S_t, x_t) \mid S_0 \right\} \right)
\]

- We add in a *pattern metric* that penalizes deviations from the historical pattern of the distribution of length of haul for each driver type

\[
\max_x \left( E \left\{ C(S, x) \right\} - \theta \ast H(x, \rho) \right)
\]

Scaling parameter

Pattern database from history

model decision variables
Pattern matching

This strategies builds on a line of research to improve our ability to match patterns using optimization models:


Pattern matching

Average LOH for Drivers of Type A

Using approximate dynamic programming and patterns

Acceptable region

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Calibration

- Matching average length of haul

![Graph showing historical maximum, simulation, and historical minimum for LOH across different capacity categories (US_SOLO, US_IC, US_TEAM)].

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Calibration

Revenue per tractor

Utilization
Validation

simulation objective function

# of drivers with attribute a

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Validation

simulation objective function

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Validation
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Policy studies

Driver Scheduling (Time-at-Home)

- Motivation: Scheduling flexibility is a trade-off of driver quality-of-life and network efficiency. A business plan to allow driver self-scheduling was piloted with potentially promising results. Prior to implementation, better analysis was needed.

- Questions: Is this feasible? Do the pilot results scale to the full transportation network? What are the cost impacts?

- Results: Original plan was only feasible at a very high cost ($30M/year). An alternate plan suggested by simulation modeling was implemented at a cost of $6M/year while achieving similar benefits.
Policy studies

- Driver Hours-of-Service (HOS) Rules
  - Motivation: Six years ago the US DOT introduced significant changes in the driver work schedule rules. Quantitative impact of these changes was hard to determine.
  - Questions: What would be the productivity impact of the changes? What steps could be taken to mitigate these effects; i.e., to either lessen or obtain compensation for them.
  - Results: The company was able to effectively negotiate adjustments in customer billing rates and freight tendering/handling procedures, leading to margin improvements of 2 to 3%.
Policy studies

- Setting Appointments
  - Motivation: A key challenge in the order booking process is how to determine both the timing and the flexibility of the load pickup and delivery appointments.
  - Questions: What is the operational impact of various different types of appointment criteria?
  - Results: Schneider negotiated and adjusted appointment criteria resulting lower customer costs, margin improvement up to 10%, and 50% reduction in late deliveries.
Policy studies

Cross Border Relay Network

» Motivation: New security-increasing border crossing (US/Canada) procedures were introduced which require special training/identification/certification of cross border drivers.

» Questions: Would a network redesign reducing the number of crossing points and border-crossing drivers be feasible? What would be the cost and service impacts?

» Results: Relying heavily on simulation analysis, a small set of relay points was established, allowing border-crossing to be concentrated with Canadian drivers. The number of drivers who had to be trained/certified was reduced by 91%, with cost avoidance of $3.8M and annual savings of $2.3M.
Policy studies

Driver Domiciles

» Motivation: Driver domiciles (home-base) significantly affect both pay rates and network efficiency. Pre-existing criteria for domicile hiring targets and pay differentials were not based on sound analysis.

» Questions: How should domicile region hiring quotas and pay differentials be set to best balance freight flows with regional employment opportunities.

» Results: Simulator-derived approximate value functions were used to provide estimates of the marginal value of drivers by type and region. These are now used to guide hiring strategies, leading to an estimated annual profit improvement of $5M.
Policy studies

Large Shipper Request

» Motivation: A large shipper asked for tighter time windows on its approximately 4,500 loads per month delivered by Schneider.

» Questions: What is the cost impact to satisfy this request? How can this impact be justified to the customer?

» Results: Using the simulator, The annual cost increase was estimated to be $1.9M. The shipper subsequently withdrew the request.