Workforce Management in Periodic Routing: Practice, Modeling and Solution Approaches

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Presentation outline

Background

An overview of related work in periodic routing

Practice

Workforce management in practice

Modeling

Periodic routing models with workforce management objectives

Solution approaches

Exploit relationships among models

Conclusions and future steps

Workforce management in periodic routing

Periodic distribution problems

Route vehicles to visit nodes over a time period (possibly with schedule choice)

Key idea: Performance improves as drivers perform the same tasks multiple times (consistency)

Customer Familiarity

Reduce the cost per visit to a customer as the frequency of visits to that customer increases

If the customer set varies significantly by day, it may be advantageous to consider a more aggregate level

Region Familiarity

Reduce the cost per visit to a region as the frequency of visits to that region increases

Workforce Management in Periodic Routing

Modeling workforce management in periodic routing

Christofides (1971), Beasley (1984), and *Wong, Beasley (1984)*
- Fixed territory strategies

Zhong, Hall, Dessouky (2004)
- Learning/forgetting behavior for drivers

Francis, Smilowitz, Tzur (2008)
- A posteriori calculation of workforce metrics

Groer, Golden, Wasil (2009)
- Constraints to enforce consistency

Smilowitz, Nowak, Jiang (2010)
- Incentives to achieve consistency

Solution approaches for periodic routing

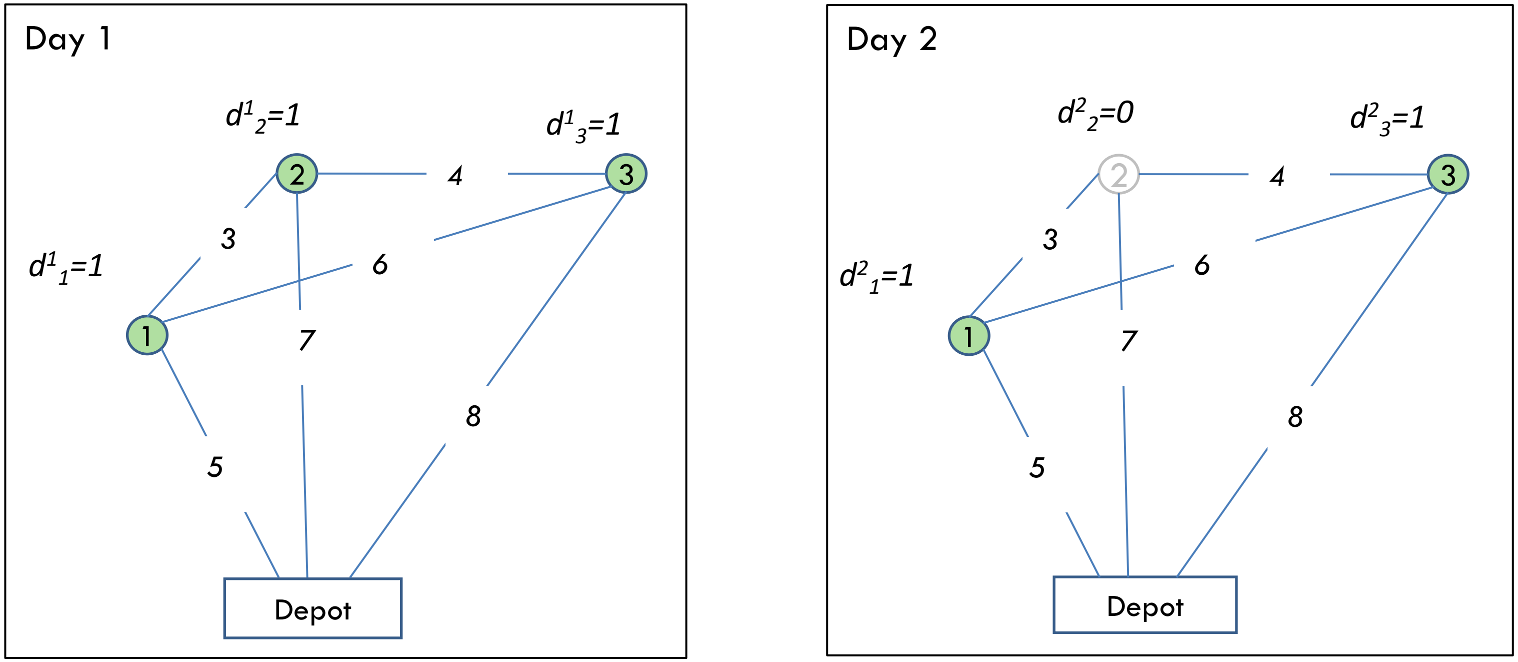
Russell & Gibbon (1991), Chao, Golden, Wasil (1995), Tan & Beasley (1984), Cordeau, Gendreau, Laporte (1997)
- Various heuristic approaches

Francis, Smilowitz, Tzur (2008)
- Exact solution approach to assignment-routing formulation

Baldacci, Bartolini, Mingozzi, Valletta (2011)
- Exact solution approach to set partitioning-like formulation based on earlier exact approach for CVRP

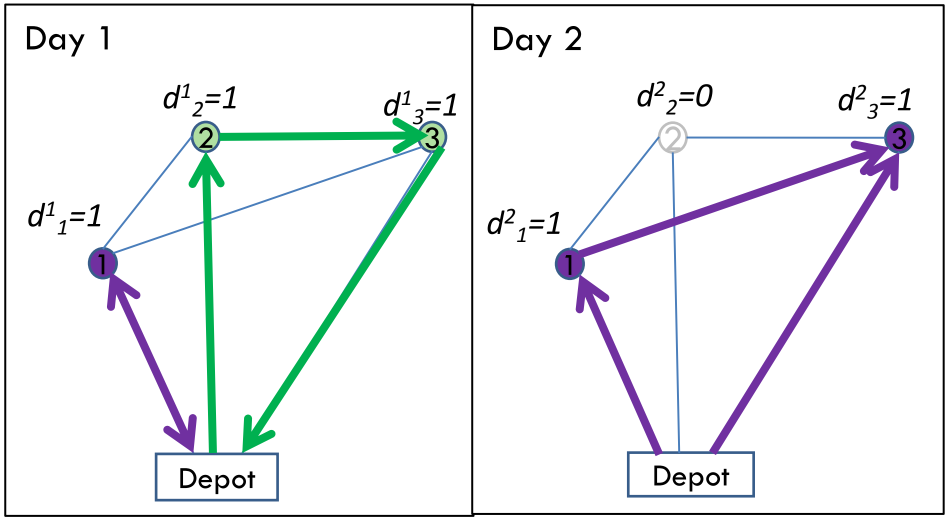
Workforce management

Assign 2 drivers to visit three nodes over a period of 2 days *, with 2 vehicles, each of capacity 2



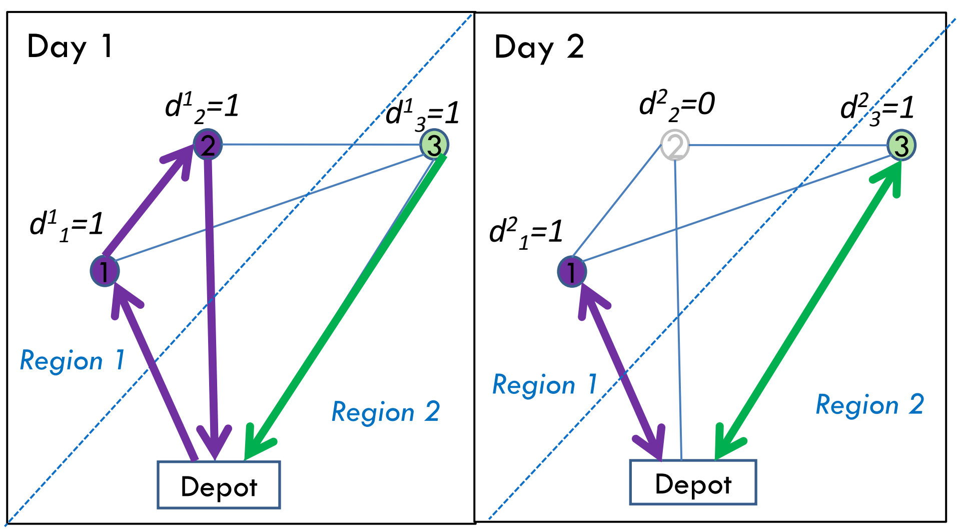
*Visitation dates for nodes are given, unlike traditional PVRP

Example



Assign 2 drivers to visit three nodes over a period of 2 days, with 2 vehicles, each of capacity 2

Min cost solution:
Use 1 driver on day 2, given low demand



Max region familiarity solution:
Partition drivers by region

Does workforce management matter and what does it cost?

"Many UPS drivers work the same route for 20 or 25 years. …**UPS drivers form a real bond with customers**...A formal program that gathers sales leads from drivers generates volume of more than 60 million packages a year, largely because **drivers take tremendous ownership of their customers and routes**.

In contrast, a major competitor reserves the right to reconfigure some drivers' routes with five days' notice, meaning their customers, service area and earnings power can change quickly."

- UPS Corp. (2006)

"While desirable to route the same drivers to the same customers each and every day, **that level of consistency can be inefficient**. As Hugh Gigante of *Appian* notes, `If we tell a customer that it costs them $100 a day to keep the same drivers servicing the same customers, **most fleets will decide it isn't worth the cost**.'"

- Partyka and Hall (2010)

PVRP model variations

- Travel Distance: PVRP(TD)
  - Minimize total travel distance across all routes
  - Problem decomposes by day (given no choice in schedule)
- Region Familiarity: PVRP(RF)
  - Maximize the number of visits by a driver to a region
  - Links driver-node assignments across days through region visit variables
- Fixed Territory: PVRP(FT)
  - Minimize total travel distance across all routes
  - Links driver-node assignments across days through fixed territory constraints

PVRP(TD)

Phase I:
Design vehicle routes (customer assignment & sequence) to minimize cost

→

Phase II:
Assign drivers to routes to achieve workforce goals

PVRP(RF)
PVRP(FT)

Single Phase:
Design vehicle routes (customer assignment & sequence) and assign drivers to routes to minimize cost and achieve workforce goals

PVRP (TD) Phase I

- Travel Distance: PVRP(TD)

$$f_{TD} = \sum_{i,j,k,t} c_{ij} x_{ijk}^{t}$$

Allocation variables **by day**

$$y_{ik}{}^{t} = \begin{cases} 1 & \text{if node } i \text{ is visited by vehicle route } k \text{ on day } t \\ 0 & \text{otherwise} \end{cases}$$

Routing variables **by day**

$$x_{ijk}{}^{t} = \begin{cases} 1 & \text{if vehicle route } k \text{ traverses arc } (i, j) \text{ on day } t \\ 0 & \text{otherwise} \end{cases}$$

PVRP (TD) Phase I model

Solve independently for each day

Minimize Travel distance

Subject to:

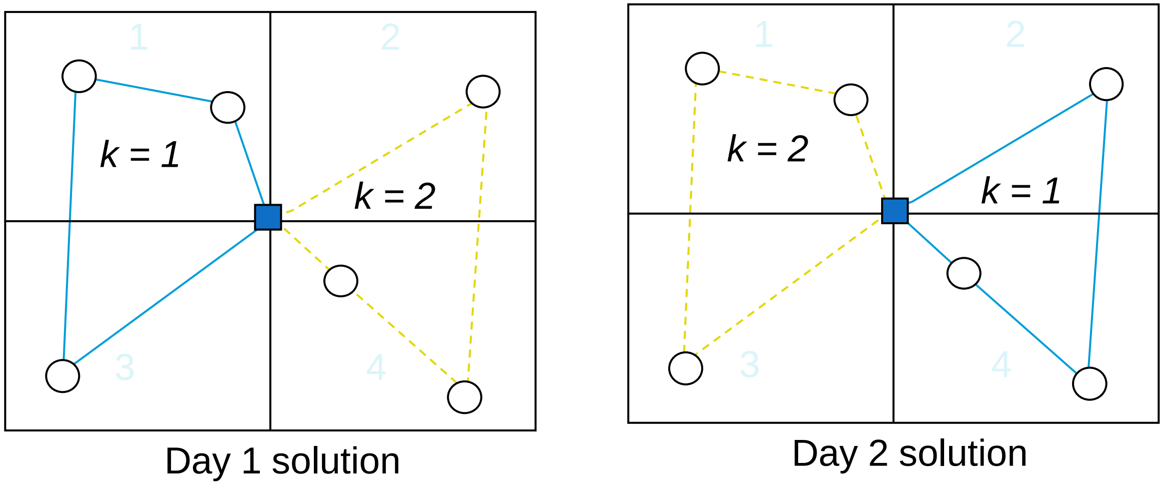
- Allocate nodes to schedules and vehicle routes $\{y\}$
  - service frequency requirement
  - capacity constraint

- Route vehicles $\{x\}$
  - balance flows
  - eliminate sub-tours

- Link allocation to routing $\{x, y\}$
  - vehicle routes must visit scheduled nodes

PVRP (TD) Phase II

In Phase I, vehicle index, *k*, is arbitrary



Assign drivers to vehicle routes, based on Francis, Smilowitz, and Tzur (2008)

$$y_{ik}^{t} = \begin{cases} 1 & \text{if node } i \text{ is visited by vehicle route } k \text{ on day } t \\ 0 & \text{otherwise} \end{cases}$$

$$\pi_{lk}^{t} = \begin{cases} 1 & \text{if driver } l \text{ is assigned to vehicle route } k \text{ on day } t \\ 0 & \text{otherwise} \end{cases}$$

PVRP (RF)

- Link driver and vehicle routes in a single model in which routes are designed and drivers are assigned to routes

Region/driver frequency variables

$$u^n_{rl(k)} = \begin{cases} 1 & \text{if region } r \text{ is visited by the driver of vehicle route } k \text{, denoted } l(k) \text{, a total of } n \text{ times in the period} \\ 0 & \text{otherwise} \end{cases}$$

- Region Familiarity: PVRP(RF)

$$f_{RF} = f_{TD} + \phi_{RF} \sum_{r,k,n} n \beta^n u^n_{rl(k)}$$

- Reduce the per-visit cost to a region, β^n, as the frequency of visits increases
- Include a weighting factor, ϕ_{RF}

$\beta^n > \beta^{n+1}$ The *per-visit cost* decreases as driver visits the region more frequently

$n\beta^n < (n+1)\beta^{n+1}$ The *total visit cost* cannot decrease with more visits

PVRP (RF) model

Minimize Travel distance + Workforce costs

Subject to:

- Allocate nodes to schedules and vehicle routes $\{y\}$
  - service frequency requirement
  - capacity constraint

- Calculate region visit frequency $\{y,u\}$

- Route vehicles $\{x\}$
  - balance flows
  - eliminate sub-tours

- Link allocation to routing $\{x, y\}$
  - vehicle routes must visit scheduled nodes

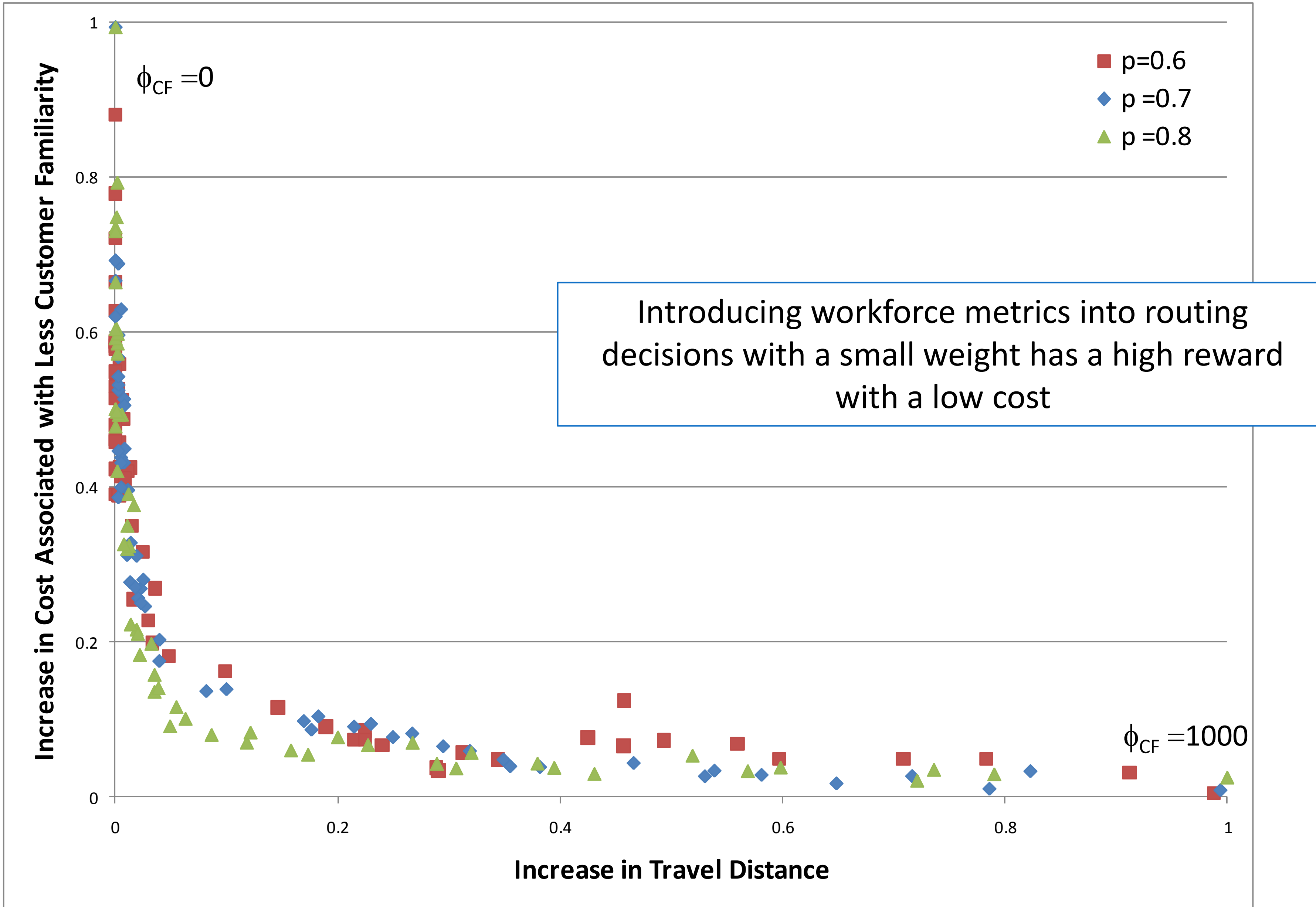
Quantifying trade-offs

- Test cases
  - Multi-day instances used by Groer, Golden, and Wasil (2009), adaptation of VRP benchmarks of Christofides and Eilon (1969)
  - Probability of service request: {0.6, 0.7, 0.8}
  - Multi-objective models: vary the importance of workforce metrics with a weight, ϕ
  - Solutions obtained with Tabu Search

- Evaluate the effectiveness of one model in terms of achieving the goals of another model
  - $\Delta_I(\mathrm{PVRP}(J_\phi))$: relative gap in the value of objective I between the PVRP solution in which J is the primary objective with weight ϕ and the minimum value of objective I

$$\Delta_{\mathrm{I}}(\mathrm{PVRP}(\mathrm{J}_\phi)) = \frac{f_{\mathrm{I}}(\mathrm{PVRP}(\mathrm{J}_\phi)) - f_{\mathrm{I}}^{\mathrm{MIN}}}{f_{\mathrm{I}}^{\mathrm{MIN}}}.$$

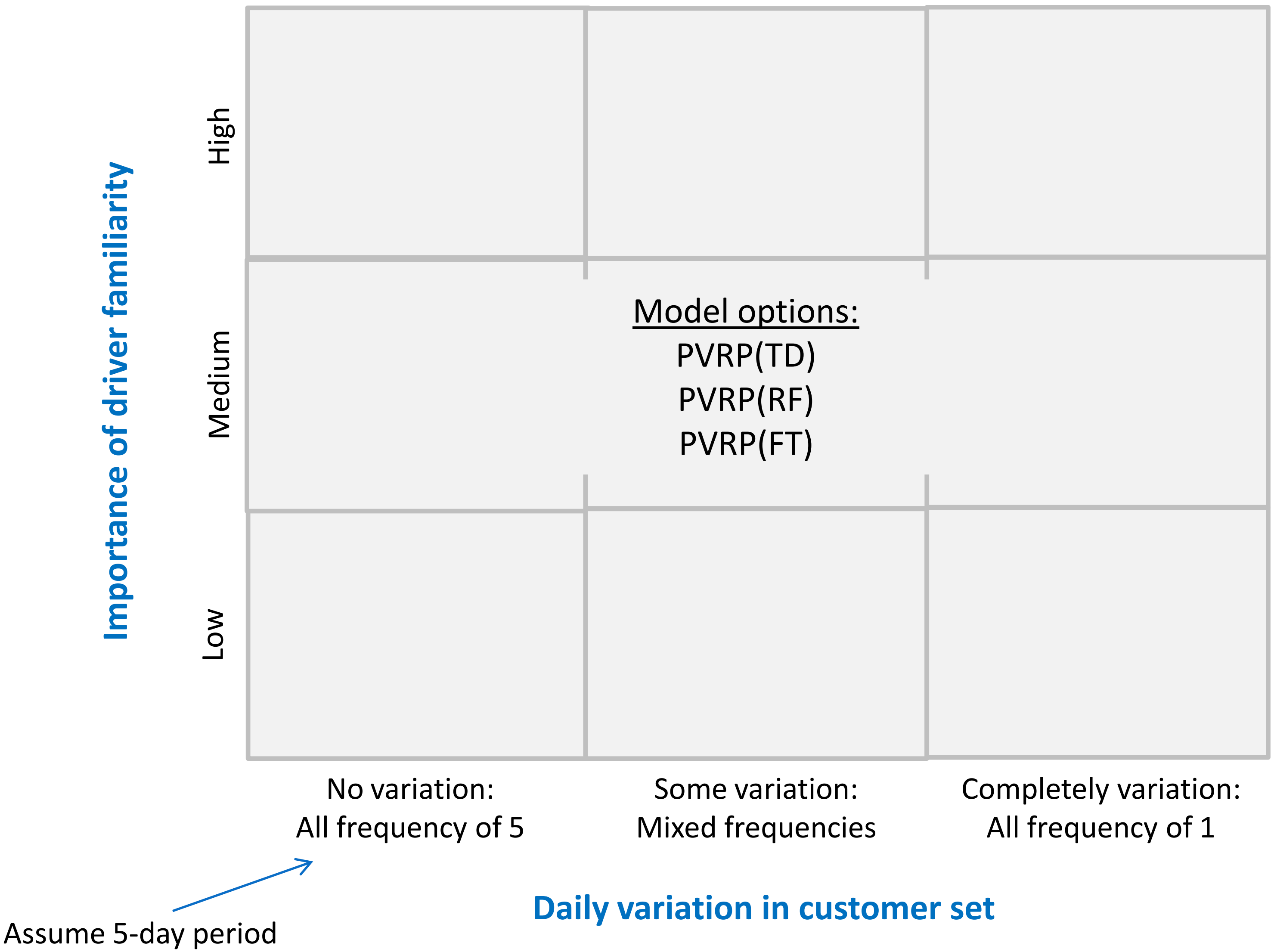
Trade-off between customer familiarity and travel distance



Observations and implementation challenges

- Introducing workforce metrics into routing decisions with a small weight has a high reward with a low cost
- Translating models to practice:
  - Similar results observed in tests with data from a major package carrier
  - Conducted interviews with carriers involved in periodic routing and software providers who develop routing software

Matching models with industry



Matching models with industry

Importance of driver familiarity	No variation: All frequency of 5	Some variation: Mixed frequencies	Completely variation: All frequency of 1
High	VRP (repeat daily)	PVRP(FT)	PVRP(FT)
Medium		PVRP(RF)	PVRP(RF)
Low		PVRP(RF) with small workforce weight	PVRP(RF) with small workforce weight or PVRP(TD)/VRP for each day

Daily variation in customer set

Matching models with industry: practitioner findings

UPS residential delivery

<u>Benefits of driver familiarity:</u> Efficiency; doorman access; revenue generation

<u>Customer characteristics:</u> Low volume; 1 stop per segment daily

<u>Challenges of driver consistency:</u> Variation in demands; balance loads

<u>Innovative ideas:</u> Core area of 3/4 drivers; subdivide into trace

Importance of driver familiarity: High / Medium / Low

VRP (repeat daily)

PVRP(FT)

PVRP(FT)

PVRP(RF)

PVRP(RF) with small workforce weight

PVRP(RF) with small workforce weight or PVRP(TD)/VRP for each day

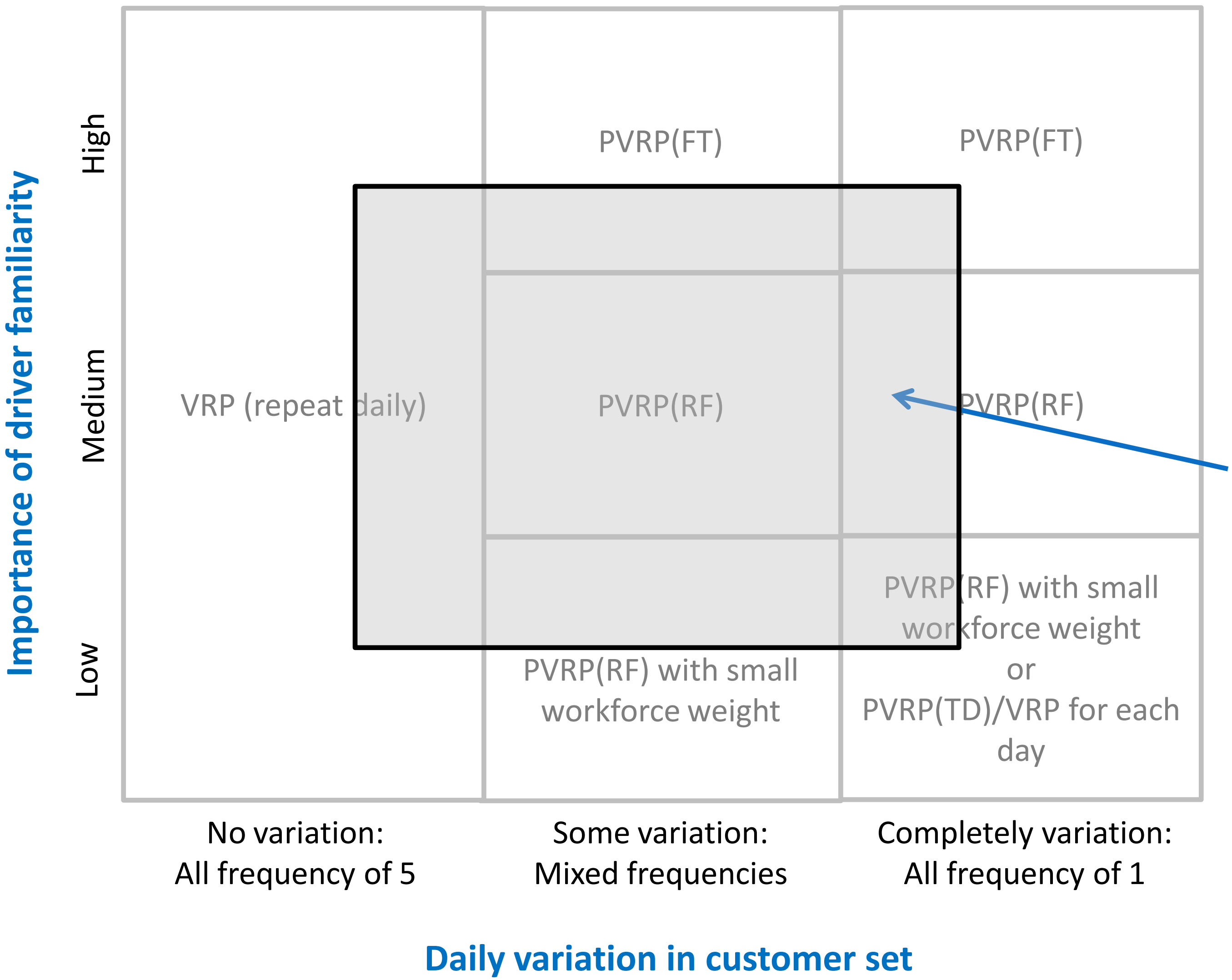
No variation: All frequency of 5

Some variation: Mixed frequencies

Completely variation: All frequency of 1

Daily variation in customer set

Modeling periodic routing: new opportunities



What happens in the gray area?

Options:

1. Easy-to-solve VRP, decomposed by day
2. Easy-to-implement Fixed territory PVRP
3. PVRP with travel and workforce costs
4. Fixed territory models with limited (and intelligently placed) flexibility

PVRP model variations: sequential solution approaches to exploit bounds

$f_I(PVRP(J))$: value of objective I for solution to model variation PVRP(J)

f_I^{MIN}: the minimum value of objective I

① **PVRP(TD)**

Decompose into independent VRP's

To obtain $f_{TD}(PVRP(TD))$

Solve with VRP heuristic:
$f_{TD}(PVRP(TD)) \geq f_{TD}^{MIN}$

Solve with VRP exact method:
$f_{TD}(PVRP(TD)) = f_{TD}^{MIN}$

To obtain $f_{RF}(PVRP(TD))$

Use matching from FST (08):
$f_{RF}(PVRP(TD)) \geq f_{RF}^{MIN}$

② **PVRP(FT)**

Solve multi-day PVRP with fixed territories

$f_{TD}(PVRP(TD)) \leq f_{TD}(PVRP(FT))$

$f_{RF}(PVRP(FT)) = f_{RF}^{MIN} \leq f_{RF}(PVRP(TD))$

③ **PVRP(RF)**

Solve multi-day PVRP with fixed territories

$f_{TD}(PVRP(TD)) \leq f_{TD}(PVRP(RF)) \leq f_{TD}(PVRP(FT))$

$f_{RF}(PVRP(FT)) \leq f_{RF}(PVRP(RF)) \leq f_{RF}(PVRP(TD))$

Exact solution approach, Francis, Smilowitz, Tzur (2008)

Lagrangian Relaxation Phase
- Relax constraints linking assignment and routing

Assignment Sub-problem (y_{ik}^{t})
- Capacitated assignment problem
- Easy to solve in practice

Routing Sub-problem (x_{ijk}^{t})
- Prize-collecting traveling salesman problem
- Use bounds when problem can't be solved

Updating Upper Bounds
- $y \rightarrow x$: time consuming but useful
- $x \rightarrow y$: easy, but often infeasible

Branch and Bound Phase
- Close the gap using information from Lagrangian re
- Given *y*'s, associated *x* sub-problem may have been solved

Observations for current work:
- Workforce variables contained within assignment sub-problem
- The LR phase does not take significant advantage of bounds from related models
- B&B phase can use bounds, but this is a small part of the solution effort
- Can we develop an approach that uses these bounds earlier?

Exact solution approach, Baldacci, Bartolini, Mingozzi, Valletta (2011)

1. Create a set partitioning-like formulation of the PVRP

2. Apply exact approach from CVRP work *(can be used for PVRP(TD))*
   (i) Compute dual solution of LP-relaxation (with added valid inequalities)
   (ii) Use dual solution to generate reduced IP
   (iii) Solve reduced IP

3. Develop relaxations of the PVRP, required for Step (i) *(applications for PVRP(RF) and PVRP(FT)?)*

4. Derive bounding principles
   (i) One relaxation involves a conversion to the CVRP

BBMV approach considers schedule choice; address the changes (simplifications) due to the lack of schedule choice

Conclusions and future steps

Practice

- Workforce management principles can be applied with a minimal impact on travel costs through multi-objective PVRP models.
- However, resulting solutions can be difficult to communicate/implement in the field.

Modeling

- We are now analyzing limited flexibility models to find solutions that come close to workforce management models with less complexity.

Solution approaches

- Exploit the relationships among models in a sequential solution approach

Extensions

- Choice in visitation dates
- Dynamic models: as drivers become more familiar with a region, more visits may be possible

Questions?