A practical time slot management and routing problem in attended home delivery

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Outline

1. Gas and water distribution
2. Study case
3. Optimization problem
4. Solution method
5. Computational results
6. Conclusions and future research directions
The context

We consider the European market of commodities that come from natural resources, specifically gas (but also electricity and water could be included).

Trading companies compete each other to sell commodities to customers.

The distribution company manages the local network.
The distribution company must provide several *Attended Home Delivery* (AHD) services to customers:

- open new gas/water meters for new buildings,
- update gas/water meters when a customer changes from a trading company to another,
- close gas/water pipes when a customer does not pay,
- ...

This is done by a set technicians that travel along the road network.
The introduction of the on-line agenda

Up to a few years ago, appointments to customers’ homes were defined by mutual agreements (phone calls) between the distribution company and the customers.

More recently, the European Community imposed the use of an on-line agenda:

- the distribution company must specify available time slot on a time table, that is published and kept updated on the web;
- trading companies fix appointments for their customers in the free time slots.
The time table we deal with

<table>
<thead>
<tr>
<th></th>
<th>Mon</th>
<th>Tue</th>
<th>Wed</th>
<th>Thu</th>
<th>Fri</th>
</tr>
</thead>
<tbody>
<tr>
<td>08:30-09:30</td>
<td>4</td>
<td>2</td>
<td></td>
<td>2</td>
<td>6</td>
</tr>
<tr>
<td>09:30-10:30</td>
<td>4</td>
<td>4</td>
<td></td>
<td>2</td>
<td>6</td>
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<tr>
<td>10:30-11:30</td>
<td>4</td>
<td>4</td>
<td></td>
<td>2</td>
<td>6</td>
</tr>
<tr>
<td>11:30-12:30</td>
<td>4</td>
<td>2</td>
<td></td>
<td>2</td>
<td>6</td>
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<tr>
<td>12:30-13:30</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>13:30-14:30</td>
<td></td>
<td></td>
<td>4</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>14:30-15:30</td>
<td>4</td>
<td></td>
<td>2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>15:30-16:30</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>17:30-18:30</td>
<td></td>
<td>4</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

- Five working *days*
- Eight *time slots* of one hour each per day
- Estimated time for one service is fixed to 30 minutes = 1 *resource* unit
- *N* resources in a time slot = *N*/2 technicians available in that slot
Study case

The company

Our study case originates from the activity of IRETI, subsidiary of IREN, a company distributing electricity, gas and water in the Italian territory.

We focus on the distribution of gas and water in the province of Reggio Emilia, that concerns around 500,000 people.

Around 12 IRETI technicians operate AHD services starting from 3 depots. A third-party logistic operator is used for peaks (fixed fee per service).
A growing activity

Number of visits to customers

Total traveled km

Before the on-line agenda

After the on-line agenda

2010

2014

2012

2013

22959

22401

24154

24741

291,719

290,362

305,864

322,569

348,870

Before the on-line agenda

After the on-line agenda

Bruck, Cordeau and Iori

ROUTE – 2016
The need for optimization

Average time to service

Average km per service
Optimization problem

Three-level optimization problem (1)

Stage 1: time table creation

Input:
- \( D \) = set of days
- \( T \) = set of time intervals
- \( M \) = set of depots
- \( Q_i \) = n. of available technicians for \( i \in M \), each serving max \( \sigma \) resources per interval
- \( R \) = set of regions, each assoc. with a depot
- \( q_r \) = expected demand, for \( r \in R \)

Aim: find a time table for each region, that is, compute

\[ u_{rdt} = \text{number of technicians working in time slot } (d, t) \text{ of region } r \]

such that expected unserved demand and routing costs are minimized
Stage 2: booking of time slots

In this stage the actual customer demand is revealed

Input:
- $\bar{u}_{rdt} =$ stage 1 solution at hand
- $J = \bigcup_{r \in R} J_r =$ set of customers
- $w_j \in \{1, 2\} =$ n. of resources required by each $j \in J$

Aim: simulate assignment of customers to time slots, that is, compute
- $a_{jrdt} = 1$ if $j$ books appointment in time slot $(d, t)$ of region $r$, $0$ otherwise

Revealed demand can be different from the expected one at stage 1

The cost of a stage 2 solution is the total unserved demand multiplied by a fee $\rho$
Three-level optimization problem (3)

Stage 3: design of the routing plan

Input:
- $\bar{a}_{jrdt} = \text{stage 2 solution at hand}$
- $G = (V, A) = \text{road network represented as a digraph}$

Aim: find a solution of minimum routing cost such that
- each route starts from a depot and returns to the same depot
- at most $Q_i$ routes are selected for each depot $i \in M$
- each technician fulfills at most $\sigma$ resources for each time slot
- each appointment is serviced by a technician
Some related AHD literature

- survey and discussion of a study case

Agatz, Campbell, Fleischmann and Savelsbergh, Time Slot Management in Attended Home Delivery, *Transportation Science* (2011)
- routing costs approximated with stars, use of incentives for low-demand slots

- static and dynamic criteria to accept/reject customer demands

- assigning time windows to customers and then construct vehicle routing
Challenges to create good-quality solutions

The problem is complex and the instances at hand are very large, so we opted to use a (meta-, math-)heuristic algorithm.

The key-issue is the cost evaluation:
- the use of quick local search procedures is not trivial
- need of a *fitness function* that penalizes features that may have a negative impact on the routing plan
- at stage 1 regions are univocally assigned to the depots. Only at stage 3 a technician may perform a task that is not associated with his/her depot
- estimation of the routing cost through a problem relaxation
Large Neighborhood Search


```plaintext
function LNS(estimatedDemands, initialSolution, simulationStrategy)
    bestSolution ← initialSolution
    bestCost ← ESTIMATESOLUTIONCOST(bestSolution, simulationStrategy)
    for it ← 0 to numIt do
        newSolution ← REPAIR(DESTROY(bestSolution, estimatedDemands))
        cost ← ESTIMATESOLUTIONCOST(newSolution, simulationStrategy)
        if cost < bestCost then UPDATEBESTSOLUTION(newSolution, cost)
    end for
    return bestSolution
end function
```
MILP model to create (and repair) solutions

Let $u_{rdt} =$ amount of resources; $v_{rdt} =$ difference in resources between two consecutive slots; $z_r =$ unserved demand

$$\begin{align*}
\text{max} & \quad \text{fitness} = \sum_{r \in R} \sum_{d \in D} \sum_{t \in T} p_{dt} u_{rdt} - \sum_{r \in R} \sum_{d \in D} \sum_{t \in T} \gamma v_{rdt} - \sum_{r \in R} \Omega z_r \\
\text{Slot popularity} & \quad \text{displaced resources} & \quad \text{unserved dem.}
\end{align*}$$

$$\sum_{d \in D} \sum_{t \in T} u_{rdt} = q_r - z_r \quad \forall r \in R$$

$$\sum_{r \in R} u_{rdt} \leq \sigma Q_i \quad \forall i \in M, d \in D, t \in T$$

Constraints linking $v_{rdt}$ and $u_{rdt}$

$$u_{rdt}, v_{rdt}, z_r \geq 0, \text{integer} \quad \forall r \in R, d \in D, t \in T$$

Easy to repair a partial solution by keeping fixed some $u_{rdt}$ values
Simulation strategies

Re-assign real-life appointments to the newly created time slots

Assume all time slots are equally popular:

1) Evenly vertical (EV): first vary hour, from early to late, and then day
2) Evenly Horizontal (EH): first vary day, from Monday to Friday, and then hour

Consider real-life information:

3) Rescheduling based (RB): assign as close as possible to the real slot
4) Popularity based (PB): assign according to real-life probabilities $p_{dt}$
Evaluate Routing Cost through a Problem Relaxation

We create a time-extended network with a set $T' = \{0, 1, ..., |T|, |T| + 1\}$ of layers. Each layer $t$ contains vertices for customers that chose an appointment at time $t$, plus duplicate copies of each depot $i \in M$. 
Evaluate routing cost through a problem relaxation

We set $x_{hk} = 1$ if arc $(h, k) \in A'$ is used and 0 otherwise, and solve a *non-fixed destination multidepot multiple traveling salesman problem* (nf-MmTSP)

$$\min \sum_{(h,k) \in A'} c_{hk} x_{hk}$$

$$\sum_{k \in V'} x_{i0k} \leq Q_i \quad \forall i \in M$$

$$\sum_{h \in V'} x_{hk} = 1 \quad \forall j \in J$$

$$\sum_{k \in V'} x_{hk} = \sum_{k \in V'} x_{kh} \quad \forall h \in V' \setminus \{i_0, i_{|T|+1}\}$$

$$\sum_{h \in S} \sum_{k \in S} x_{hk} \geq \left[ \sum_{h \in S} \frac{w_h}{\sigma} \right] \quad \forall S \subseteq J'_t, \bar{S} \in J'_{t-1} : t \in T$$

$$x_{hk} \in \{0, 1\} \quad \forall (h, k) \in A'$$

Fixed destination MmTSP can be solved with infeasible path-constraints, but disregarded because of increased time and small cost variation
Implementation and Instances

Algorithms implemented in C++ and run on a PC with Intel Core i7 at 3.40 GHz.
Cplex 12.6.2 used with 8 threads and default options.
We used a set of 52 benchmark instances referring to the weeks of 2012.
We computed real traveling distances using OpenStreetMap.

Expected demand is a key issue:
At tempted strategies

Several runs were performed according to different estimation of the demands:

- current: estimation of the cost by the company using the existing time table (fixed table that uses base as expected demand but is integrated on-the-fly when needed)
- LNS-base demand: LNS using base as expected demand to produce weekly time tables
- LNS-avg demand: LNS using avg 2010-13 as expected demand
- LNS-a priori demand: LNS using the exact 2012 demand (utopic scenario)
## Average results

<table>
<thead>
<tr>
<th>month</th>
<th>#</th>
<th>current cost</th>
<th>LNS - base demand cost</th>
<th>LNS - base demand gap</th>
<th>LNS - base demand sec</th>
<th>LNS - avg demand cost</th>
<th>LNS - avg demand gap</th>
<th>LNS - avg demand sec</th>
<th>LNS - a priori demand cost</th>
<th>LNS - a priori demand gap</th>
<th>LNS - a priori demand sec</th>
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</thead>
<tbody>
<tr>
<td>Jan</td>
<td>5</td>
<td>6037</td>
<td>5653</td>
<td>-6.4%</td>
<td>276</td>
<td>5603</td>
<td>-7.2%</td>
<td>142</td>
<td>5329</td>
<td>-11.7%</td>
<td>267</td>
</tr>
<tr>
<td>Feb</td>
<td>4</td>
<td>5718</td>
<td>5431</td>
<td>-5.0%</td>
<td>275</td>
<td>5196</td>
<td>-9.1%</td>
<td>281</td>
<td>5032</td>
<td>-12.0%</td>
<td>256</td>
</tr>
<tr>
<td>Mar</td>
<td>4</td>
<td>6407</td>
<td>6142</td>
<td>-4.1%</td>
<td>276</td>
<td>5712</td>
<td>-10.8%</td>
<td>268</td>
<td>5538</td>
<td>-13.6%</td>
<td>283</td>
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<tr>
<td>Apr</td>
<td>5</td>
<td>5426</td>
<td>5046</td>
<td>-7.0%</td>
<td>272</td>
<td>5134</td>
<td>-5.4%</td>
<td>281</td>
<td>4927</td>
<td>-9.2%</td>
<td>268</td>
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<tr>
<td>May</td>
<td>4</td>
<td>6917</td>
<td>6501</td>
<td>-6.0%</td>
<td>279</td>
<td>5941</td>
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<td>278</td>
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<td>279</td>
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<td>283</td>
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<td>281</td>
<td>5912</td>
<td>-13.6%</td>
<td>267</td>
</tr>
<tr>
<td>Aug</td>
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<td>5176</td>
<td>4744</td>
<td>-8.3%</td>
<td>272</td>
<td>4881</td>
<td>-5.7%</td>
<td>277</td>
<td>4656</td>
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<tr>
<td>Sep</td>
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<td>275</td>
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<td>Dec</td>
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<td>5647</td>
<td>-19.1%</td>
<td>175</td>
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<tr>
<td><strong>avg</strong></td>
<td></td>
<td><strong>6769</strong></td>
<td><strong>6433</strong></td>
<td><strong>-5.1%</strong></td>
<td><strong>276</strong></td>
<td><strong>6019</strong></td>
<td><strong>-10.6%</strong></td>
<td><strong>239</strong></td>
<td><strong>5723</strong></td>
<td><strong>-14.9%</strong></td>
<td><strong>245</strong></td>
</tr>
</tbody>
</table>
Average results

![Graph showing average results over months]

- **Current**
- LNS-base demand
- LNS-avg demand
- LNS-a priori demand

The graph indicates the average cost across different months, with peaks and troughs that may correlate with seasonal or other external factors. The data points suggest variability in costs, with some months showing higher costs than others.
### Results under different simulation strategies

<table>
<thead>
<tr>
<th>simulation</th>
<th>current</th>
<th>LNS - base demand</th>
<th>LNS - avg demand</th>
<th>LNS - a priori demand</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>cost</td>
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<td>gap</td>
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<td>PB</td>
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<tr>
<td>avg</td>
<td>6769</td>
<td>6433</td>
<td>-5.1%</td>
<td>276</td>
</tr>
</tbody>
</table>
Conclusions and future research directions

LNS very effective in reducing costs under different simulated scenarios. It uses just a few iterations of a heavy search guided by MILP models.

The most interesting future research direction comes from a (yet another) new European law on gas and electricity distribution (about to be applied in Italy), which imposes new smart meters for automatic data collection.

- they can be closed by long distance if user does not pay
- send data directly to warehouse?
- send them to local antennas (where to locate them)?
- collect data with vehicles?
- integration with residual AHD activities? ...
Thank you very much for your attention