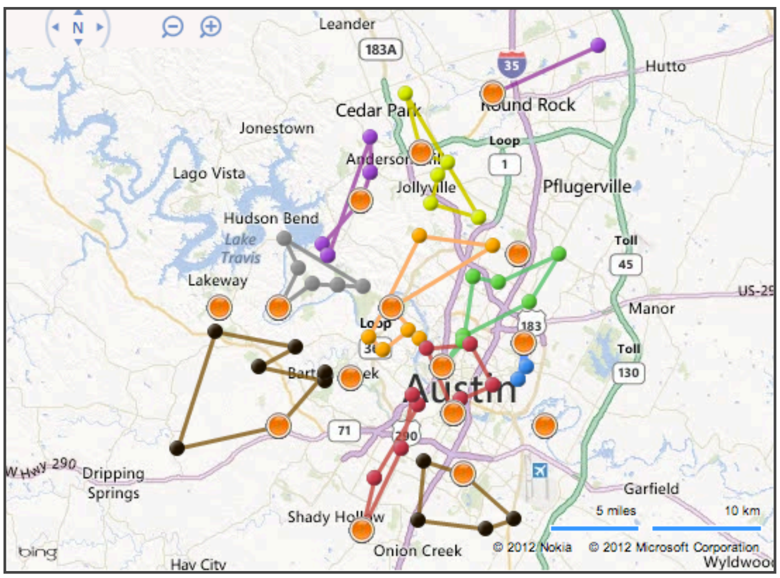
OPTIMIZED HOME CARE SCHEDULING AND ROUTING

A White Paper for Home Care Executives and Operations Managers

ALGORITHM-BASED OPTIMIZATION FOR SOLVING THE SCHEDULING AND ROUTING PROBLEMS IN HOME CARE



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Introduction

Many home health executives have come to consider mileage reimbursement as simply a cost of doing business. Believing such expenditures are like salaries, some agency leaders have decided nothing strategic can be done to diminish this line item on their budgets. Likewise, they view patient scheduling as a hands-on, time intensive endeavor but generally have not considered re-engineering the process in order to improve day-to-day operational outcomes.

Many organizations have tried to implement the use of web-based mapping services such as Google™ Maps or MapQuest™, some have purchased global positioning systems (GPS) for employees, and others have even gone so far as to invest in fleets of company cars. While each of these efforts may generate some degree of cost savings, no approach offers an optimal solution for reducing unnecessary mileage reimbursement and maximizing resource utilization.

The basic problem with the above methods is that they only solve the routing problem for a single person and do not take into account an organization's entire clinical staff. In the field of mathematics, these highly complex delivery and resource utilization problems are called Vehicle Routing Problems (VRPs).

VRPs have been examined since the 1950s, but the unique business and patient care demands of home care generally render those solutions insufficient when trying to calculate a feasible schedule for home care clinicians. This white paper proposes a solution by extending the traditional VRP to take into account the additional criteria needed to solve the scheduling and routing problem for home care organizations. The proposed solution provides agencies dramatic savings while also allowing them to focus on quality patient outcomes.

While the solution described in this paper is based on traditional home care services, it can be easily applied to other home care industries such as hospice, private-duty, and house call physicians as well.

Vehicle Routing Problems

VRPs are programming problems typically used by transportation organizations—like FedEx™ or UPS™—that have a fleet of vehicles and need to distribute goods or services to one or multiple locations. The goal of applying VRP techniques is to minimize the cost of distributing the goods to the given destinations.

If all the vehicles depart from a central location (depot), the problem is known as a Single-Depot VRP. The Single-Depot VRP is the "classic" version of the problem. When there are multiple locations from which the vehicles depart, then the problem is considered a Multi-Depot VRP.

There are numerous other VRP variations. For example: problems that handle vehicles with limited capacity to carry goods, limited time to perform delivery, and limited time during which the customer is available for delivery. The VRP that most closely represents home care is multi-depot (clinicians are typically starting from their homes), capacitated (clinicians have limited availability), and with time-windows (patients may have a window of availability during which they can be seen or prefer to be seen). It is generally considered one of the most difficult problems to solve in the VRP class of problems.

Problem Difficulty

To some, vehicle routing problems may seem quite straightforward—just try all the combinations of visits to find out which is shortest or cheapest. However, solving even the smallest VRP takes a prohibitive amount of time on the fastest supercomputers. As an example, for a simple delivery with a single driver and no constraints or external factors, the following routing combinations must be considered:

4 delivery stops	24 possible solutions
5 delivery stops	120 possible solutions
6 delivery stops	720 possible solutions

You can see just how quickly the number of combinations grows, even for this simple case. The number of routing combinations for just 25 patients is 15,511,200,000,000,000,000,000,000. It quickly becomes apparent that it is not humanly possible for home health schedulers or clinicians to find efficient solutions to their scheduling problems.

One way to address these challenging problems is by developing a series of simulations that get you close to the absolute solution to the problem, but without the time investment necessary to solve the problem exactly. By using a class of problem solving, known as search heuristics, a computer can get to a suitable answer that is optimal to within 1% of the precise mathematical solution, but at less than 1/10,000th of the computation time required.

Instead of mathematically solving a very complex problem, search heuristics aim to model the problem and, through experience, calculate a suitable, though not absolutely ideal, answer to the problem. By contemplating a series of these heuristic models, the outcomes can be evaluated, and the solution that comes closest to reaching the established goal can be selected as the "best" answer to the problem at hand.

Scheduling and Routing in Home Care

Much of the time, home care organizations assume that travel expense is just part of the cost of doing business, rather than looking at it as an opportunity to reduce outlays. While it is a fact that mileage is a significant, inherent home care expense, it is also true that the opportunity exists to save money if the scheduling and routing problems can be solved.

Scheduling Problems

Often, patient visits are assigned to clinicians either days or weeks in advance. Schedulers might consider a clinician's general geographic location and discipline during this "assignment" process, but with little to no consideration given to efficiency or overall productivity.

Home care schedulers are responsible for ensuring that all patients with orders have clinicians assigned to provide their care. Schedulers are quite busy, so their focus is on ensuring clinicians are assigned to cover all patient visits and generally do not have the time to create the "perfect" schedule that meets all the patient needs and while minimizing staff utilization and optimizing routing.

Routing Problems

In the typical scenario, after the visit assignment process, the clinician determines what day the patient should be seen. With so many combinations, it is impossible for a clinician to choose the optimal sequence of visits to maximize productivity and minimize mileage reimbursement for the organization. Clinicians usually "eyeball" the best order in which to see patients while accounting for patient needs. For example, a clinician would want to make every effort to place a patient first in a care route knowing the patient is fasting in preparation for lab work.

If there are no overriding patient needs, clinicians may base their treatment routes on their own needs—not necessarily what is best for their organization. For instance, a clinician may opt to see a patient last in a treatment route because that patient lives nearest her child's school. Seeing the patient last means it will be convenient to pick up her daughter when school is over.

Levels of Optimization

A new concept has surfaced to help industry leaders step outside of the boundaries of those narrowing contribution margins. This concept is known as Resource Optimization. The idea is simple: schedule and route clinicians among patients in a manner that provides optimal patient care while also ensuring optimal savings to the organization.

To illustrate this concept, we define five levels of optimization designated Level 0 to Level 4. Nearly all organizations operate somewhere along this spectrum. Agencies that move from lower to higher levels of optimization reap significant rewards. The Levels of Optimization are defined as follows:

Level 0: No Optimization

- An organization that is not using any software for routing or scheduling is making no attempt at optimization.
- Clinicians are scheduled based on "tribal knowledge" or a rough "eyeball" of the proximity of staff to the patient's home.

Level 1: Point-to-Point Optimization

- The visit order is determined by the scheduler or clinician and is therefore not optimal. The driving directions from one point to another using a GPS or web-based mapping service are optimal.
- This level can provide a basic "fraud audit" for mileage that ensures the mileage reported by clinicians for reimbursement is the same as the mileage actually driven.

Level 2: Visit Sequencing

- More advanced mileage audit tools exist allowing organizations to calculate the optimal treatment order for a given clinician among given patients on a given day. This technique is called Visit Sequencing.

- This is the classic Traveling Salesman Problem (TSP).

Level 3: Visit Assignment and Sequencing

- At Level 3, organizations can go a step beyond Level 2 and find the optimal clinician to see scheduled patients. In this situation, the scheduler no longer spends time assigning clinicians to visit slots.

- An enhanced scheduling and routing solution identifies the optimal clinician (based on geographic location and travel route) to see the patients for a given day to provide care in the optimal order.

Level 4: Optimal Weekly Schedule

- What Level 3 Optimization does for one day, Level 4 does for an entire week. Level 4 Optimization allows agencies to optimize all visits for all clinicians.

- Once the scheduler plots the visit frequencies, the Level 4 workflow varies from a typical scheduling workflow. Instead of the scheduler assigning clinicians to perform visits, the system assigns optimal clinicians to perform visits. Instead of the clinicians determining on what days and in what order they will perform their visits, the system determines the optimal days and the optimal order in which they will be performed.

Scheduling and Routing Based on VRP Optimization

The solution proposed here involves adapting the well-known VRP solutions to meet the needs of the home care industry, through a set of constraints. We will define a set of constraints that help the optimization engine find a feasible solution to meet the goals of the home care organization.

Since solving a VRP problem exactly can require an enormous amount of computational power, we instead utilize a set of heuristic algorithms that converge on an "optimal" solution in a much shorter amount of time. The basic idea is to simulate a large number of potential solutions (candidates) and rate the "quality" of each candidate. The simulation is time-boxed to provide numerous possible solutions for evaluation, given a fixed amount of acceptable time to spend solving the problem.

Each candidate's quality is calculated from a number of limitations or parameters called constraints. In a VRP solution, the lower the quality the better. For example: if we assume the only consideration for quality is distance then the candidate with the lowest distance would considered the best.

Home care, however, is not so simple that we can only take distance into consideration. While distance is important, other constraints play a major role in determining which clinicians will be assigned visits during the scheduling process. We have defined two basic categories of constraints for home care: hard constraints and soft constraints. Constraints are used with penalty multipliers to modify the quality of a candidate. Hard constraints are penalized considerably more than soft constraints, which act more as preferences. A quality score is broken into two portions, cost and distance, and each has a corresponding weight associated with it. The Quality Score for each candidate is calculated as a function of the equation below:

$$\boxed{\text{Quality} : (\text{Cost} * \text{Penalties}_{\text{cost}} * \text{Weight}_{\text{cost}}) + (\text{Distance} * \text{Penalties}_{\text{distance}} * \text{Weight}_{\text{distance}})}$$

Hard Constraints

Hard constraints are those constraints that, if not met, will result in an infeasible solution. For example, if a physical therapist is assigned to perform a skilled nursing visit, that would be an unacceptable solution and the result is deemed infeasible. For our purposes, we have identified the following hard constraints that, at a minimum, ensure a feasible solution is found.

1. **Service Type**: the assigned staff must be capable of performing the scheduled service (visit).

2. **Assigned User**: if specified, the only person that can perform the visit is the assigned user.

3. **Clinician Availability**: all visits must be performed within the available time of the clinician. This is an example of time-window constraint.

4. **Patient Availability**: the visit must be performed within the specified time the patient is available.

5. **Clinician Capacity**: the maximum number of visits that can be assigned to an individual clinician on a given day (regardless of availability).

Soft Constraints

Soft constraints are not required for a feasible solution, but can be thought of as preferences that influence the optimization engine's results to meet the desired goals of the user.

1. **Cost-vs-Distance Ratio**: Determines the cost and distance weight portion used in calculating the quality score. If reducing overall cost is the focus, then the preference would be set toward cost (at the expense of greater mileage). If the focus is on productivity, then the preference is set toward mileage reduction (at the expense of greater cost).

2. **Degree Preferences**: Prefers one degree type over another. For example: LVN staff may be favored over RN staff since they generally are less expensive to employ. Organizations watching their budgets may choose to set their preferences toward LVN/LPN and PTA. Those focusing more on outcomes may set their preferences toward RN and PT.

3. **Pay Type Preferences**: Prefers one pay type over another. Managers may ask the optimization system to prefer salaried clinicians over fee-for-service (FFS) when assigning visits, with the goal of ensuring salaried clinicians' schedules are filled with preference over scheduling any visits with FFS clinicians. These constraints are usually expressed as a penalty. For example: if an agency prefers salaried staff, the salaried penalty might be 1.0 (no penalty), FFS penalty might be 1.5 (50% penalty) and Contract penalty might be 2 (100% penalty).

4. **Leg Lengths**: Limits the amount of driving between visits. There are two leg length constraints: average and maximum. They can be used to limit the average and maximum length of any leg in a provider's care route. The idea is to ensure "long-distance sensitive" clinicians (such as FFS staff) remain viable care solutions for your organizations by reducing the drive time between visits.

Simple Quality Calculation

Below is a simple example of how quality might be calculated for 2 possible nurses for a given patient visit. Assume the following parameters:

1. Clinician A is a salaried RN who lives 10 miles from the patient's home.

2. Clinician B is a FFS LVN who lives 10 miles from the patient's home.

3. Cost to Distance ratio is 100% distance (base the score only on the distance rather than on cost).

4. FFS penalty = 1.5 (assumes we prefer salaried staff over FFS staff).

5. RN penalty = 1.3 (assumes we prefer LVN staff over RN staff).

$$\text{Quality}_A : 10_{\text{miles}} * 1.3_{\text{RN penalty}} * 1.0_{\text{Salaried penalty}} = \mathbf{13}$$

$$\text{Quality}_B : 10_{\text{miles}} * 1.0_{\text{LVN penalty}} * 1.5_{\text{FFS penalty}} = \mathbf{15}$$

Even though LVNs were favored over RNs (by a 1.3 penalty), salaried clinicians were favored even more over FFS clinicians (by a 1.5 penalty). Therefore, the optimization engine is more likely to develop a solution that selects clinician A to perform the visit since that clinician had the lower (better) quality (lesser penalty) score.

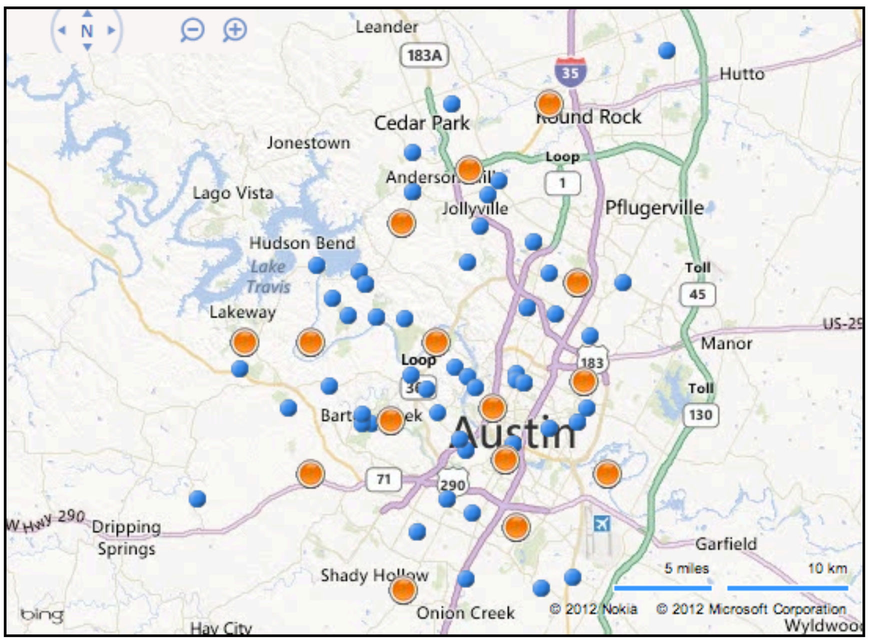
Optimization Examples

Many times an organization's goal isn't just to reduce mileage, but to improve other metrics as well. A VRP optimization engine can be designed in such a way as to solve a wide range of problems.

Below, we present several example problems that were solved using a VRP optimization system. The solutions generally show the effects of one set of preferences over another and should give you a good idea of the power and flexibility of such a system.

In all the examples that follow, there is a population of 15 skilled nursing clinicians available to be scheduled, and 63 skilled nursing visits that need to be scheduled. The clinicians each have 8 hours (480 minutes) of daily availability, which includes visit and drive time. The set of clinicians includes a distribution of salaried, FFS, and Contract staff with varied costs per visit. Some clinicians are reimbursed for mileage and some are not. In addition, the clinician sample includes a distribution of RN vs LVN staff. The examples use level 3 optimization models for comparison purposes.

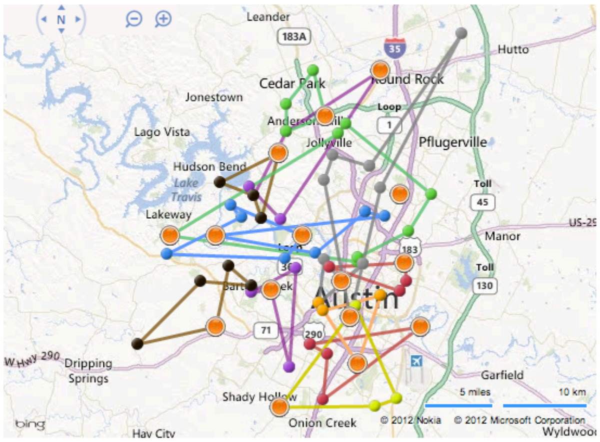
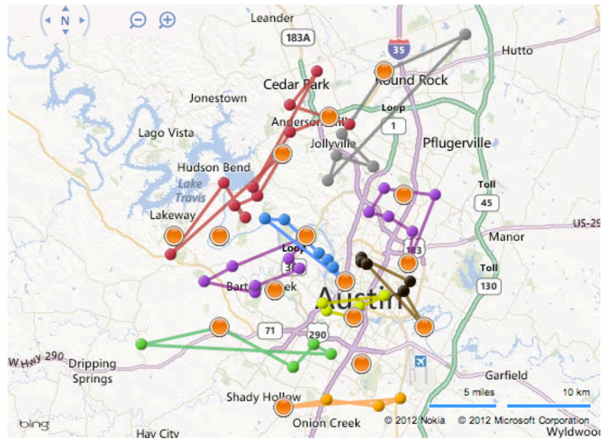
In the image below, blue dots represent patients, and orange dots represent clinicians.



While each example derives an optimal solution, each solution is different, based on the constraints used in the model. These differences demonstrate that system users can influence solution parameters to meet the goals of different organizations. These examples are not meant to be exhaustive, but rather to show the power and flexibility of an algorithm-based optimization scheduling system.

Example 1: Basic Schedule Optimization

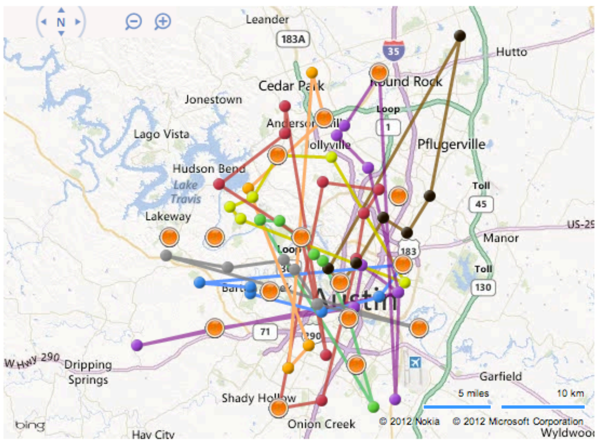
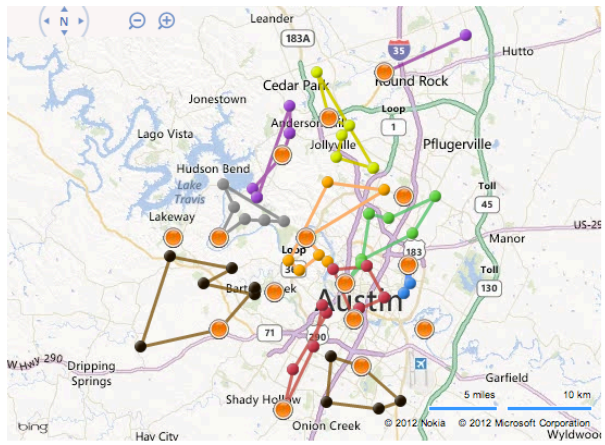
The first example compares a non-optimized schedule against a schedule using level 3 optimization. The non-optimized solution is the typical "eyeball" approach. The optimized solution uses the default preferences (no weights applied, 50/50 split on cost weighting vs distance weighting in the quality scores).

<table>
<tr><th>NON-OPTIMIZED</th><th>OPTIMIZED</th></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>Constraints
None</td><td>Constraints
Cost to Distance Ratio: 50% Distance, 50% Cost
Average Leg Distance: 20 miles
Maximum Leg Distance: 30 miles</td></tr>
<tr><td>Results
Distance: 487.31 miles
Staff Used: 15</td><td>Results
Distance: 315.74 miles
Staff Used: 10
Staff Mix: 9 RN Salaried, 1 LVN Salaried
Unused: 3 RN FFS, 1 RN Salaried, 1 RN Contract</td></tr>
</table>

Analysis: The optimized solution is about 70% shorter and used four less staff than the non-optimized solution. No preferential constraints were applied other than cost-to-distance ratio, average and maximum leg lengths.

Example 2: Optimization Based on Cost vs Distance

This example demonstrates two spectrums of optimization: cost and distance. The first example demonstrated a 50/50 split so that the quality calculation took into account both cost and distance in determining the optimal solution. Below are shown the extreme cases where the optimization is determined 100% based on cost or 100% based on distance. Keep in mind, both are optimal solutions, it just depends on the goal of the organization to determine which is a better fit.

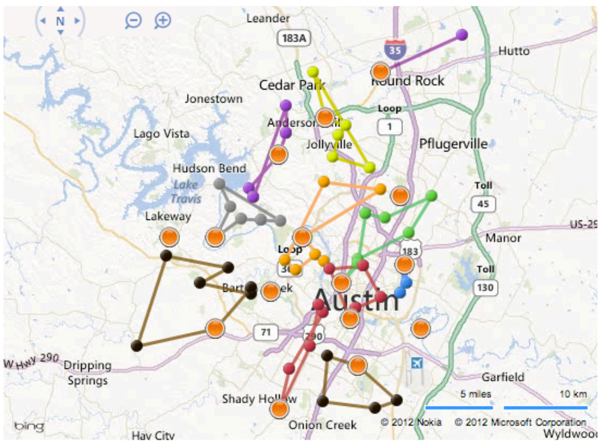
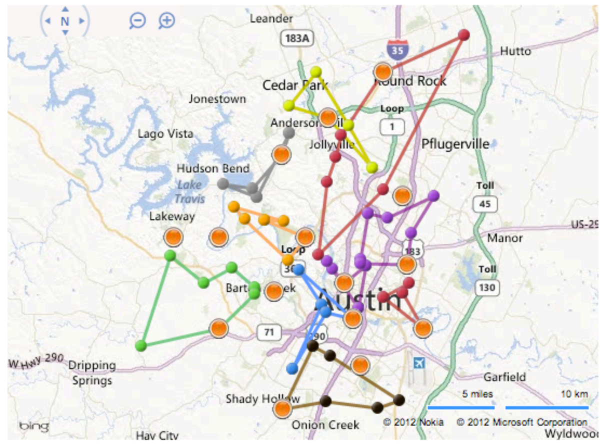
<table>
<tr><th>COST BASED</th><th>DISTANCE BASED</th></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>Constraints
Cost to Distance Ratio: 100% Cost
Average Leg Distance: 20 miles
Maximum Leg Distance: 30 miles</td><td>Constraints
Cost to Distance Ratio: 100% Distance
Average Leg Distance: 20 miles
Maximum Leg Distance: 30 miles</td></tr>
<tr><td>Results
Distance: 574.47 miles
Cost: $221.70
Staff Used: 10
Unused: 3 RN FFS, 1 RN Contract, 1 RN Salaried</td><td>Results
Distance: 286.75 miles
Cost: $1,084.52
Staff Used: 11
Unused: 2 RN Salaried, 2 LVN Salaried</td></tr>
</table>

Analysis: While is doesn't look like the 100%-cost-based solution is very optimal, keep in mind the constraints called for optimizing based on lowest cost, not distance. Therefore, it's not a surprise to see that all the staff used were salaried since they do not incur a marginal per-visit cost. Most of the salaried staff in the sample are reimbursed for mileage.

Also note that the total mileage was significantly higher than in the 100%-distance-based solution—twice as much in fact. This variation occurs because the cost-based model doesn't take into account any distance factors in the quality calculation. Generally, the best solutions are somewhat of a mix between the two extremes.

Example 3: Maximize Salaried Staff Usage

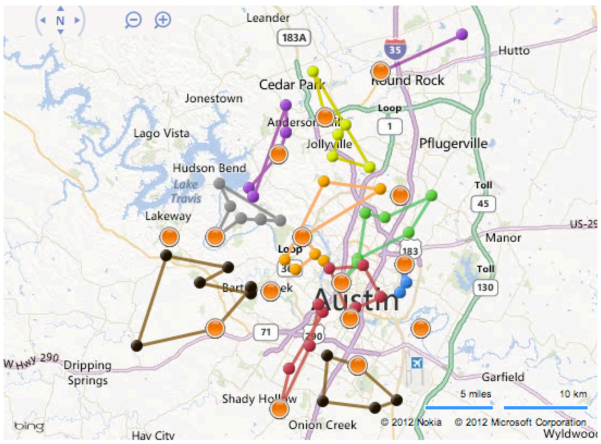
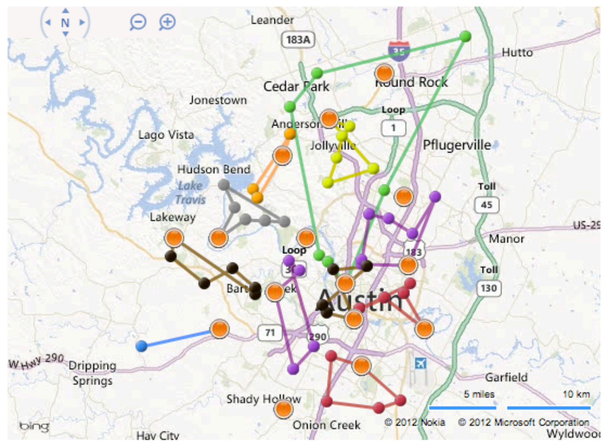
Many agencies use salaried staff to perform patient visits. Using salaried staff provides several advantages, however there is also the problem of making sure they are used to the maximum potential (since their salary is paid no matter how many visits they perform). What follows is an example of a model configuration that favors salaried staff, but the preferential constraints could be set to favor FFS, Contract or any other pay type defined.

<table>
<tr><th>ORIGINAL DISTANCE BASED</th><th>DISTANCE + SALARIED PREFERRED</th></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>Constraints
Cost to Distance Ratio: 100% Distance
Salaried, FFS & Contract Preference: 1.0
Average Leg Distance: 20 miles
Maximum Leg Distance: 30 miles</td><td>Constraints
Cost to Distance Ratio: 100% Distance
Salaried Preference: 1.0
FFS & Contract Preference: 3.0
Average Leg Distance: 20 miles
Maximum Leg Distance: 30 miles</td></tr>
<tr><td>Results
Distance: 286.75 miles
Staff Used: 11
Unused: 2 RN Salaried, 2 LVN Salaried</td><td>Results
Distance: 305.73 miles
Staff Used: 10
Unused: 3 RN FFS, 2 RN Contract</td></tr>
</table>

Analysis: The original distance-based solution solved the problem by using a mix of 11 staff, but left 4 salaried nurses unused. By increasing the FFS and Contact penalty constraint on the new model, it helped the model work all the salaried staff onto the schedule. In addition to using 1 less person, the model ensured that all the unused staff were either FFS or Contract.

Example 4: Minor Degree vs Major Degree Preferences

If an organization has a number of minor degreed staff (LVN, PTA, etc.) that can perform a certain set of visits, it is usually advantageous to utilize them fully for their cost profile. In this case, there are a number of ways to influence the optimization outcome in a similar direction. For instance, instead of preferring LVN, we could set the cost preference a little higher. This approach would in effect prefer use of less expensive staff when possible which would usually be a LVN or PTA.

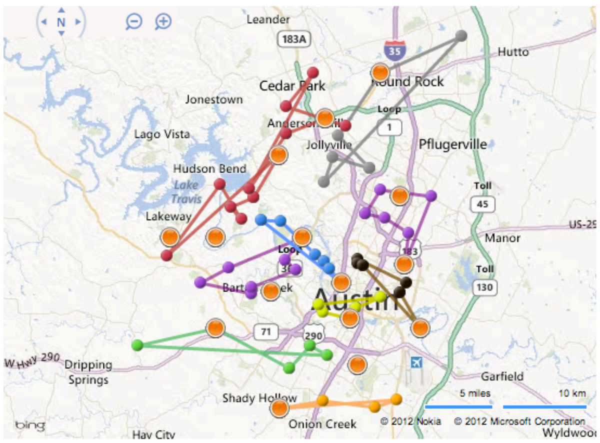
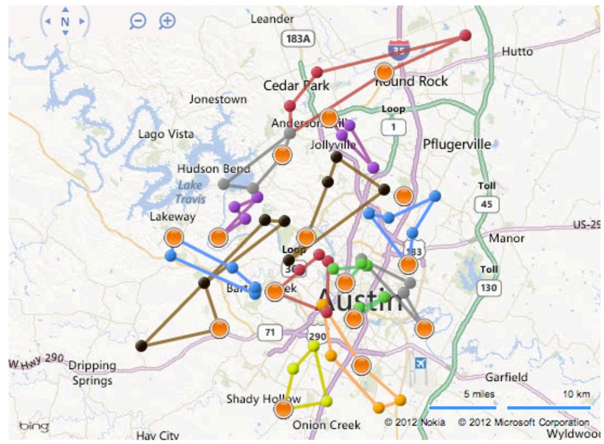
<table>
<tr><th>ORIGINAL DISTANCE BASED</th><th>DISTANCE BASED + LVN PREFERRED</th></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>Constraints
Cost to Distance Ratio: 100% Distance
Average Leg Distance: 20 miles
Maximum Leg Distance: 30 miles
RN & LVN Penalty: 1.0 (no penalty)</td><td>Constraints
Cost to Distance Ratio: 100% Distance
Average Leg Distance: 20 miles
Maximum Leg Distance: 30 miles
LVN Penalty: 1.0 (no penalty)
RN Penalty: 2.0</td></tr>
<tr><td>Results
Distance: 286.75 miles
Staff Used: 11
Unused: 2 RN Salaried, 2 LVN Salaried</td><td>Results
Distance: 317.67 miles
Staff Used: 11
Unused: 4 RN Salaried</td></tr>
</table>

Analysis: The original solution had 2 LVN clinicians that were unused. By adding a slight penalty to RN staff, LVN staff offer better quality scores, and thus are more likely to be used in the final solution.

The result of the “LVN preferred” model shows that, with the RN constraint added, the LVN staff were included in the optimized schedule.

Example 5: Balance Schedules Among Staff

Each of the previous examples utilized fewer staff than the total number available. Sometimes, an organization may prefer to distribute the visit load equally among all available staff. We can satisfy this goal by limiting the maximum number of visits allowed per day per clinician. In this example, we will set the maximum capacity to 4 visits.

ORIGINAL 50/50 SPLIT	50/50 + BALANCED SCHEDULE
	
Constraints Cost to Distance Ratio: 50% Distance, 50% Cost Average Leg Distance: 20 miles Maximum Leg Distance: 30 miles Maximum Capacity: N/A	**Constraints** Cost to Distance Ratio: 50% Distance, 50% Cost Average Leg Distance: 20 miles Maximum Leg Distance: 30 miles Maximum Capacity: 4 visits
Results Distance: 315.74 miles Staff Used: 10 Avg. Visits/Staff: 6.3	**Results** Distance: 340.92 miles Staff Used: 15 Avg. Visits/Staff: 4.2

Analysis: By setting the maximum capacity to 4, all the staff are utilized in calculating an optimal solution. The resulting schedule is much more balanced, in comparison to the original optimization. Most of the staff were assigned 4 visits but a few received 5. There was an increase in mileage, but that was to be expected since we required the engine to use everyone, even if their inclusion in the model wasn't optimal.

Organizational Benefits

Improved Patient Outcomes

With less time spent traveling and more time in their schedules, clinicians could allocate more time per patient to focus on improved outcomes. Leaders may choose to implement new patient care programs or simply allow staff to dedicate more time to improving outcomes where they are not performing to objectives.

Continuity of Care

Optimized scheduling can be used alongside an organization's existing "care team" model, or a geographic care team can be formed to ensure the patient is seeing a small set of clinicians for each visit. This approach builds familiarity with the patient and improves continuity of care.

Increase Your Contribution Margin

Some agency managers will preferentially fill the schedules for their salaried staff versus their FFS staff. The coupling of a Level 2 or Level 3 optimization solution with a Pay Type preferential constraint offers strategic thinkers an opportunity to increase contribution margins by increasing productivity and decreasing variable costs.

Make Your Staff Happy and Improve Cash Flow

By implementing optimization strategies, your clinical staff can provide the required visits in less time because they are traveling significantly fewer miles. Less travel means they can finish work and complete their documentation earlier. Timely documentation can impact your billing statistics such as the number of days until the Request for Anticipated Payment (RAP) is submitted. Timely RAPs directly impact an organization's cash flow.

Shift the Balance of Power

No longer are agency executives held hostage by the looming threat of clinician shortages or the increasing cost of mileage reimbursement. Implementing a routing optimization solution allows organizations to regain some operational control from the clinicians and schedulers.

Promote Your Green Agenda

Organizations that work smart and implement optimized routing solutions can lay claim to a higher degree of environmental awareness. Cutting mileage reimbursement by over 75% shows your agency's commitment to decreasing its carbon footprint.

Conclusion

The application of well-known vehicle routing problems combined with home-care-specific constraints and preferences allows organizations to significantly reduce the driving distance and resources needed to fulfill their visit requirements. The use of a flexible optimization engine makes it possible to craft a solution that fits the goals of virtually any home care provider. Also, because the algorithms are compatible with existing clinical care teams, providers can maintain continuity of care at a lower cost.

Many home care executives and managers feel that they are drowning in regulation and demand pressures. Those who have had to balance staffing shortages, shrinking profit margins, and the cost of providing care will likely agree that the decision to take advantage of a resource optimization tool is an easy one. Optimization allows agencies to provide the same quality of patient care with fewer staff while cutting mileage reimbursement. The ability to do more with less—much more—can help drive any organizational turn-around or growth initiative to a successful outcome.