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Leveraging Academic Partnerships to Improve Logistics at Nonprofit Organizations

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Introduction

Nonprofit organizations face a variety of barriers that impede the adoption of advanced technological tools (Eisinger 2002). Primarily, advanced technologies are often expensive, complicated to utilize, and difficult to customize to meet firms' unique needs (Thomas and Kopczak 2005). Because nonprofit firms typically operate with extremely limited financial margins (Shearer and Carpentier 2015), organizations that can overcome these barriers and optimize their operations through the employment of advanced technologies stand to benefit greatly. To overcome these barriers, nonprofit firms might attempt to raise funds via donations to pay for commercial technologies or they may solicit technology donations directly from commercial firms (Corder 2001). Alternatively, nonprofit organizations have increasingly collaborated with other nonprofit organizations to leverage the pooled resources of the combined organizations (AbouAssi, Makhlouf and Whalen 2016). A less common collaborative approach is to partner with academic researchers willing to donate their time and skills to develop a technological solution. While commercial firms and academic partners may both have expertise in applying advanced technologies to problems, an academic partner, without profit motivations, might potentially provide access to advanced technologies at a lower cost. This research note details a project utilizing this approach: leveraging a collaboration between a nonprofit organization and a team of academics, a low-cost tool was developed to allow organizations to effectively schedule vehicle logistics. The tool (1) uses general computing hardware and software that is already deployed in most organizations resulting in it being radically low cost (effectively free); (2) handles the real world constraints present in moderately complex logistics environments; and (3) is easy to use for non-technical, non-programmers as the potential users at nonprofit organizations may include volunteers with varying technical skillsets, which can potentially impact the adoption of new technologies (Evans and Clarke 2010).

Efficient vehicle utilization is critical for many community based organizations that utilize fleets to pick up and deliver community donations or to provide transportation services for community members without vehicles (Bartholdi, Platzman, Collins, and Warden 1983; Poole, Ferguson, DiNitto, and Schwab 2002). In the commercial world, shippers and logistics firms have seen tremendous gains in fleet efficiency from using advanced vehicle route optimization tools (United Parcel Service 2016). However, these tools typically require substantial financial investments, limiting their adoption by nonprofit organizations. Although free and low cost applications exist to solve many versions of the vehicle routing problem, these tools often fail to accommodate the realities of moderately complex environments — e.g. delivery windows, stop order precedence, and dynamic local specific requirements. Typical commercial solutions, that consider these planning complexities, are expensive and therefore not widely used by nonprofit organizations. This is a significant problem since many humanitarian and nonprofit organizations frequently face sophisticated fleet related challenges, including vehicle routing.

The tool we developed can determine near-optimal vehicle routings for any organization engaged in these types of operations using technologies readily available to most nonprofit organizations. To demonstrate the system's adaptability to applied environments, we prototyped the system at the Idaho Foodbank. In addition to being a test case, working with the foodbank generated several refinements that increased the usability of the system. The foodbank's operations are analogous to those at many nonprofit organizations – they operate a fleet of vehicles, often using volunteer drivers, to pick up donations and distribute them to at-need members of the population. After refining the tool, it was also successfully utilized by a local branch of the Meals on Wheels Association of America.

As long as nonprofit organizations continue to play an integral role in delivering assistance and humanitarian aid to those in need (Berner and O'Brien 2004), tools that improve the efficiency of these efforts, such as the one described in this research note, will be valuable assets. These improvements in efficiency are particularly critical in an era of limited or diminishing government support for assistance programs (Daponte and Bade 2006). Therefore, the definitive goal and intent of this nonprofit / academic partnership is to make the tool available, free of charge, to any interested nonprofit organizations.

An Approach for Nonprofit and Academic Collaboration

We utilized a version of the Waterfall model of software development to approach this project. In the Waterfall approach, the user requirements are first analyzed, then the system is designed and developed, followed by testing and finally deployment (Verzuh 2015).

Targeted Client for Tool Usability Testing

The Idaho Foodbank manages food donations and distributions to over 100,000 of Idaho's citizens each month. The foodbank operates a small fleet of vehicles whose operations must be carefully coordinated to ensure that food contributions are picked up from donors and delivered to distribution locations in a timely and efficient manner. Drivers, some of whom are volunteers, pick up donated food items and drop them off to local community distribution centers. Those centers then provide individuals with food. Due to budget limitations at the inception of our study, the foodbank's transportation managers had been manually scheduling vehicle operations without the use of software optimization tools. Our target client was a choice of convenience, as they were in the city in which two of the authors live. However, we hope that similar organizations are inspired by this project to seek out collaboration with partners in academia.

User Requirements

As part of the project we conducted interviews with two humanitarian organizations in which delivery and pick up operations are central to the mission. In line with existing research, both organizations cited transportation issues as substantial barriers to their operations (Rapp and Whitfield 1999; Snavely and Tracy 2000). Both organizations were planning routes manually at the time (although one of them had an aborted implementation of a commercial computerized system in the past). They recognized the improvements that an automated system could bring in terms of more efficient vehicle utilization, better driver utilization, and a less time consuming planning process.

Based on our interviews, we identified a number of design requirements that the solution must meet:

1. Produce near optimal routings quickly
2. Accommodate pick-up and delivery windows (times when individual locations are available or unavailable for pick-ups or deliveries).
3. Accommodate stop order precedence relationships among locations
4. Provide turn by turn driving instructions to drivers
5. Allow easy addition or deletion of stops and rearranging of precedent relationships of stops
6. Operate on fairly ubiquitous computing technology—i.e., spreadsheet, such as Microsoft Excel and internet connection (dial-up, Ethernet).
7. Allows storage of route information and stop information (e.g., special instructions to driver for location)

We investigated existing commercially available tools: Dedicated mathematical tools provide effective optimization engines; however, those tools require advanced user skills to manually enter the travel matrix data and constraint formulations. We also examined a number of free online tools including Google Maps, MapQuest, FindTheBestRoute.com, and My Route Online (of which, the latter three include route optimization tools) and found that while these tools offer automatic connectivity to travel time and driving directions databases, they limit the number of stops on a route and do not permit the inclusion of time windows and stop order precedence relationships. Furthermore, many of the free online tools do not allow users to store data for repeated usage, which forces a user to reenter the data for a route every time that tool is used.

System Design and Development

A routing tool requires five main elements: i) a data source of driving times between locations and an interface to that data, ii) a user interface to facilitate the inputting of route information and instructions, iii) a travel matrix element to collect and store travel times and driving directions, iv) a route optimizer, and v) an interface to present the optimized route and driving instructions to the user. Having detailed driving instructions in hand improves the efficiency of volunteer drivers, which is critical as volunteers have been shown to be extremely valuable assets for nonprofit organizations (Govekar and Govekar 2002). We decided to explore if a tool incorporating all of these elements could be developed using a combination of MS Excel worksheets and Excel's Visual Basic for Applications (VBA) coding language. We expand upon each of the five required elements of the tool now.

Data Source and Data Interface

Research identified existing application program interfaces (APIs) that permit MS Excel users to query online mapping databases, specifically Google Maps and MapQuest Open Data. Both services permit the retrieval of driving time and turn by turn direction data into MS Excel. Additionally, the use of the APIs is free (though MapQuest does require registration to retrieve a unique key). A comparison of the two services identified advantages unique to both: Google Maps had more complete worldwide coverage (driving directions are available for 245 countries) but they limit a user to 2,500 queries in a 24 hour period. MapQuest Open Data offers unlimited queries, however the mapping data is open-sourced, which we found to result in varying levels of precision. Both services offer annual subscriptions which increase the query limits and data quality, but the prices of these subscriptions violate our low/no cost goal. To allow users to take advantage of each services' particular benefits, we decide to include functionality in our tool to allow users to choose between using the MapQuest Open Data or Google Maps APIs. With this challenge solved, we developed the overall architecture of the tool (depicted in Fig. 1).

<< Insert Figure 1 about here >>

User Input Interface

A user interface, shown in Fig. 2, was created in Excel in order to permit users to easily enter data related to stops on a route, including the location name, the street address, available time windows, predecessor stops, and instructions specific to a stop. The user interface incorporates configuration pushbuttons that allow users to select between one-way or round trip routes, faster or robust route optimization (which is discussed in more detail later in this article), and using MapQuest Open Data or Google Maps data. Functionality to start the optimizer or reset the tool is also included. Notice that no coding or other technical expertise is require of the user, per our design. As researchers, we are familiar with encoding data, heuristics, routing and scheduling heuristics, but users typically just want to enter their data (e.g., delivery addresses), push a button, and have the solution automatically presented in an easy to understand format.

<< Insert Figure 2 about here >>

Travel Data Storage

An Excel worksheet stores the driving time and turn by turn direction information between each pair of stops on a route. By storing the data in a worksheet, users may add or remove stops from a route and re-optimize the route even when an internet connection is not available (as long as those stops existed in a route that was planned earlier with an internet connection to Google or MapQuest). This feature was critical, as it allows drivers that carry a laptop or tablet to efficiently respond to changes that may occur during a workday.

When the user initiates the program by pressing the “Click to Optimize Route” button, the program first queries each address using the selected API to allow the user to validate the addresses. This step was added after we discovered that an incorrect street address may be returned in cases where the user entered address does not exactly match the format of the address used by the mapping service (e.g. the entry of “State St” instead of “W State St” may return an incorrect address).

Once the addresses are validated, the program examines the location pairing information already stored in the data worksheet to determine if the information for any new addresses pairs needs to be retrieved. The program then uses retrieves and saves the point to point driving time and turn by turn directions between the new location pairs so that every possible location pairing is stored in the data worksheet. To reduce the amount of stored data, we initially only queried the driving time between two locations once (for a single direction). However, during testing we quickly realized that in urban locations, with numerous one way streets, the driving time may vary dramatically depending on which direction you travel between two locations.

Improved Vehicle Routing

Numerous optimization methods, all of which can quickly and effectively operate on desktop computers, have been developed over the past three decades. We determined that a genetic algorithm (GA) would be the most effective optimization technique for our application due to the ability of GAs to quickly solve complex optimization problems such as routing or batch sizing (Holland 1998; Stockton and Quinn 1993). A genetic algorithm emulates the breeding, mutation, and natural selections processes that a species might encounter, but with a population of problem solutions that compete based on their goodness to solve the problem at hand. The GA minimizes the total trip duration which includes driving time, waiting time, and time spent at each location. A route with a lower total trip duration is considered to be a more “fit” solution. A GA does not guarantee the optimal route sequence will be found, but is a fast method to produce very good (near optimal or optimal) solutions for complex problems such as vehicle routing. The GA for this system was coded as a VBA module within the Excel spreadsheet and is run by users simply by clicking a button, so no knowledge of its complexities or programming is required of the humanitarian organization in order to realize the benefits of the tool.

A route sequence that violates either the precedence order set by the user, or the hard time window at a stop, is assigned a very large penalty (specifically 2,400 hours is added to the trip duration for precedent violation and for missing the time window, that route is delayed until that stop is open again tomorrow making it an unlikely “best” solution). In similar optimization problems, time windows can be deemed “soft” with smaller penalties were assigned for arriving too early or too late (see Yu and Yang 2011 and Xu, Yan, and Li 2011); however, the foodbank required strict adherence to the time windows, hence our inclusion of the large penalty function.

The GA uses an evolutionary process in which up to 1,000 generations of solutions are created and evaluated. In a single generation, through a process that combines potential routing solutions created in a prior generation (breeding of two solutions) and possible mutation (a route may randomly have the order of two stops interchanged), the algorithm creates 100 new possible routing solutions which are scored for fitness. As mentioned previously, a route’s fitness score is equal to the total route duration. After scoring is complete, the GA then repeats the process and builds a new generation as long as 1,000 total generations or 200 generations without any improvement have not passed. When either of those criterion are satisfied, the GA picks the fittest solution (the quickest time to cover the route) and generates the detailed driver instructions for that route.

During testing it was discovered that the GA intermittently produced less than ideal routings when it became stuck on a local optima (i.e. a local optima is a route slightly faster than similar routings, but a radically different from the optimal route.) To address this, we tried a modified version of the program that conducts several distinct runs of the

GA, where each run begins with a new randomly generated initial population of all new routes. The best single solution generated by these multiple runs was selected at the best routing solution to present to the user. This breaks away from the normal convergence that occurs over time when using a GA. This approach successfully eliminated the local optima issue; however, we then had to determine that "best" number of GA runs to conduct trading off solution quality with generation time. A simulation was performed in which we applied the GA to routes varying from 5 to 11 stops (11 being the largest route that we could fully enumerate to find the optimal solution in a practical timeframe), changing the number of GA runs applied to a route from 1 up to 15. After 100 iterations at each number of GA runs, we found that a step change improvement in the solutions' nearness to optimality occurred when the number of runs was increased from two to three. Modest additional improvement occurred beyond 10 runs. These findings led us to add a configuration button to allow users to choose between running the GA three times to generate a "Faster" solution and running it up to ten times to generate a "Robust" solution.

Driving Directions and Instructions Output

The GA-determined best route, along with turn by turn driving directions, is presented in a separate tab in the Excel tool. Any special instructions regarding a pickup, delivery or time required to be spent for a location to open are included in the directions. Fig. 3 shows a sample of the route instructions. Notice that the drive time is 1 hour and 24 minutes, while total route time is 3 hours and 26 minutes – the difference being the sum of the waiting times and pickup or drop off times at each stop. Also of note in this example is that the first stop after the origin does not open until 6:30am, so the driver must wait from arrival at 6:11am until 6:30am. The penalty is just the addition of 19 minutes of non-driving, non-delivery time.

<< Insert Figure 3 about here >>

<u>Testing and Deployment</u>

Initial Deployment

We tested the tools on a number of the Foodbank's routes. To test the nearness to optimality of our GA produced solution, we applied the tool to one of the Foodbank's shortest routes, which contained only 9 stops – which was a small enough number of stops to permit full enumeration in a relatively short time period. Full enumeration requires trying every possible order of stops – for this example we calculated the route time for all 362,880 possible location stop sequences to find the lowest possible time to compare to what our GA found. We found that the GA's route sequence was the optimal route (in a matter of a few minutes, our GA found the same shortest possible route that would take many hours to fully enumerate). To further validate GA generated routings, as well as the feasibility and quality of the driving directions, we physically drove two test routes. For each test route, we first drove using the route sequence and instructions manually generated by the scheduler and then re-drove it using the GA route sequence and instructions. In the first field test the driving time and distance for a 21 stop route were both reduced by 14 percent using the GA route sequence. In the second field test (not depicted), the GA route sequence for a 9 stop route reduced the driving time from 35 to 25 minutes (28 percent less) and distance from 11 to 8.5 miles (23 percent less).

As a final validation of the tool, it was tested on one of the foodbank's primary routes (consisting of 15 stops). Compared to the sequence that the foodbank had been employing, driving time was reduced by 15 percent. The system also reduced planning time from 30 minutes to 10 minutes (most of which was spent entering the data). Using the "Faster" solution option, the 15 stop test route was optimized in 90 seconds while finding a "Robust" solution for a more involved 30 stop route required about 12 minutes of computing time. In practice, the planner at The Idaho Food Bank runs the "Faster" setting most often as it rapidly produces routes shorter in duration than those previously developed manually.

Second Deployment

In addition to the Idaho Foodbank, we also have given our tool to a local Meals on Wheels program. The Meals on Wheels Association of America is a not-for-profit organization that delivers nearly one million meals per day across the United States (Meals on Wheels 2015). Fortunately, the local Meals on Wheels program's requirements were a subset of those of the Idaho Food Bank (specifically, they needed route optimization but they did not need pickup, dropoff, precedence orders, nor hard time windows). This allowed us to supply a very similar tool, with several features unused (hidden from the user's view).

We applied the tool to 11 major routes that Meals on Wheels' volunteer drivers navigate on a weekly basis. The original planned route time for all routes was 462 minutes. After using our tool on the "faster" setting, the planned routes had a total route time of 392 minutes. This equated to a 14 percent reduction in the driving time to deliver the same meals to the same seniors. Additionally, this reduction in driving time also reduced gas consumption and volunteer fatigue, while getting the meals to their recipients more quickly.

Conclusions and Future Work

The paper demonstrates that academic researchers can help nonprofit organizations by applying their knowledge of advanced methods and technology capabilities to real problems faced by these organizations. While similar or even more advanced solutions may exist for commercial enterprises that have deep pockets, a nonprofit organization, operating at the edge of its financial margins, will benefit greatly from even modest efficiency improvements. Both of the initial users of this tool realized substantial improvements in their fleet efficiency (i.e. the overall driving time required to service pick-up and delivery routes for food donations and deliveries was reduced by approximately 14%) and a corresponding reduction in route planning times. Additional tangible benefits to the organization were lower gas expenses, reduced wear and tear on vehicles, and less exposure to risk on the road. Further, it is intuitive that enabling volunteers to do more service in less time can raise morale and enhance the volunteer recruitment process.

To enhance the tool, we are currently adding the capability to incorporate real-time traffic and road closure data into the routings (which is currently available in over 60 countries). We hope this feature will make the tool useful to humanitarian organizations involved in disaster recovery operations where road availability may be compromised. Once these enhancements are completed, we plan to make the tool available, free of charge, to any interested nonprofit organization.

If a nonprofit organization has the choice between an expensive perfect technological solution or no solution at all, they will often be forced to choose the latter due to budgetary limitations. However, this not need to be a dichotomy as there is a middle ground that we, as academic researchers, can volunteer our time and expertise to help nonprofit organizations access lower-cost (or free) solutions that help these organizations operate more. Nonprofit organizations typically do not the resources required to support expensive technology adoption programs, but following the simple steps outlined in this note, we believe with advanced technology and researchers willing to lend a hand, we can help feed the world!

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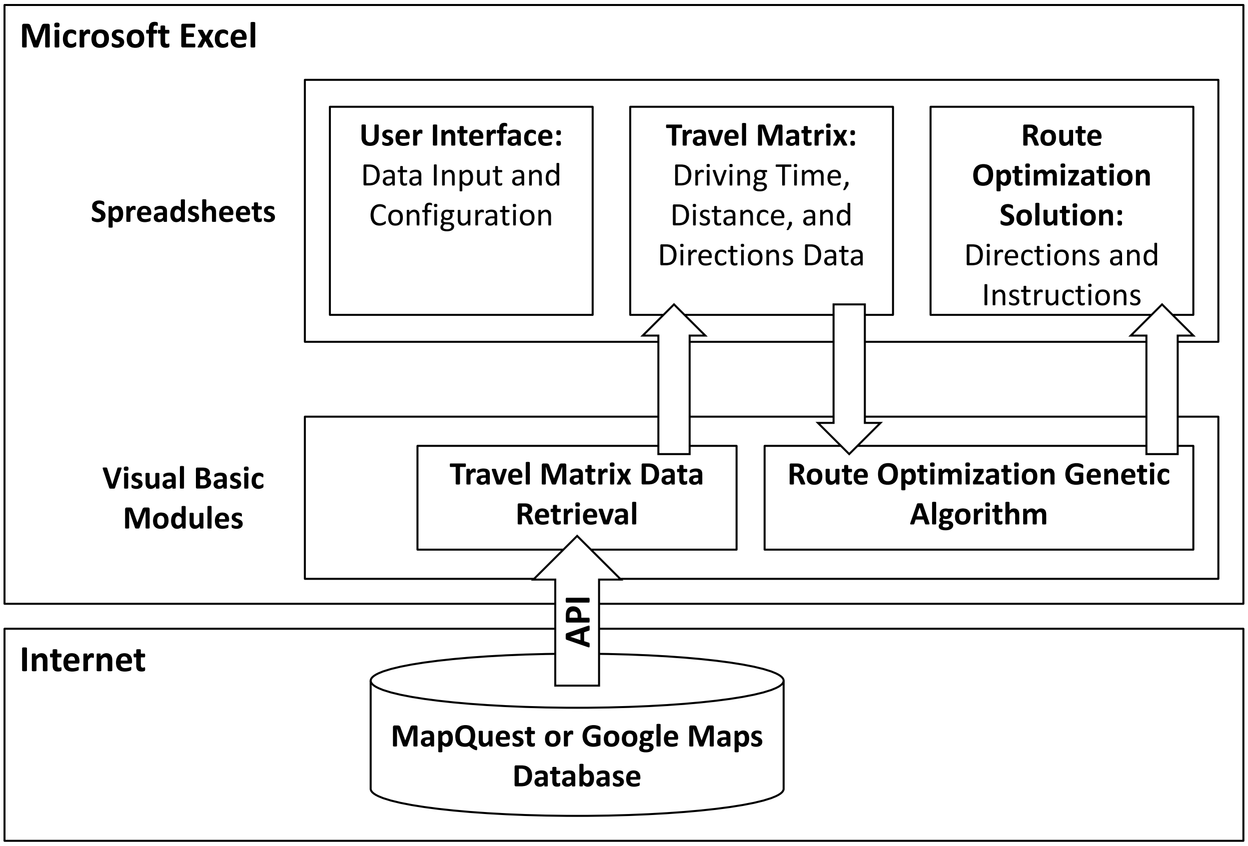
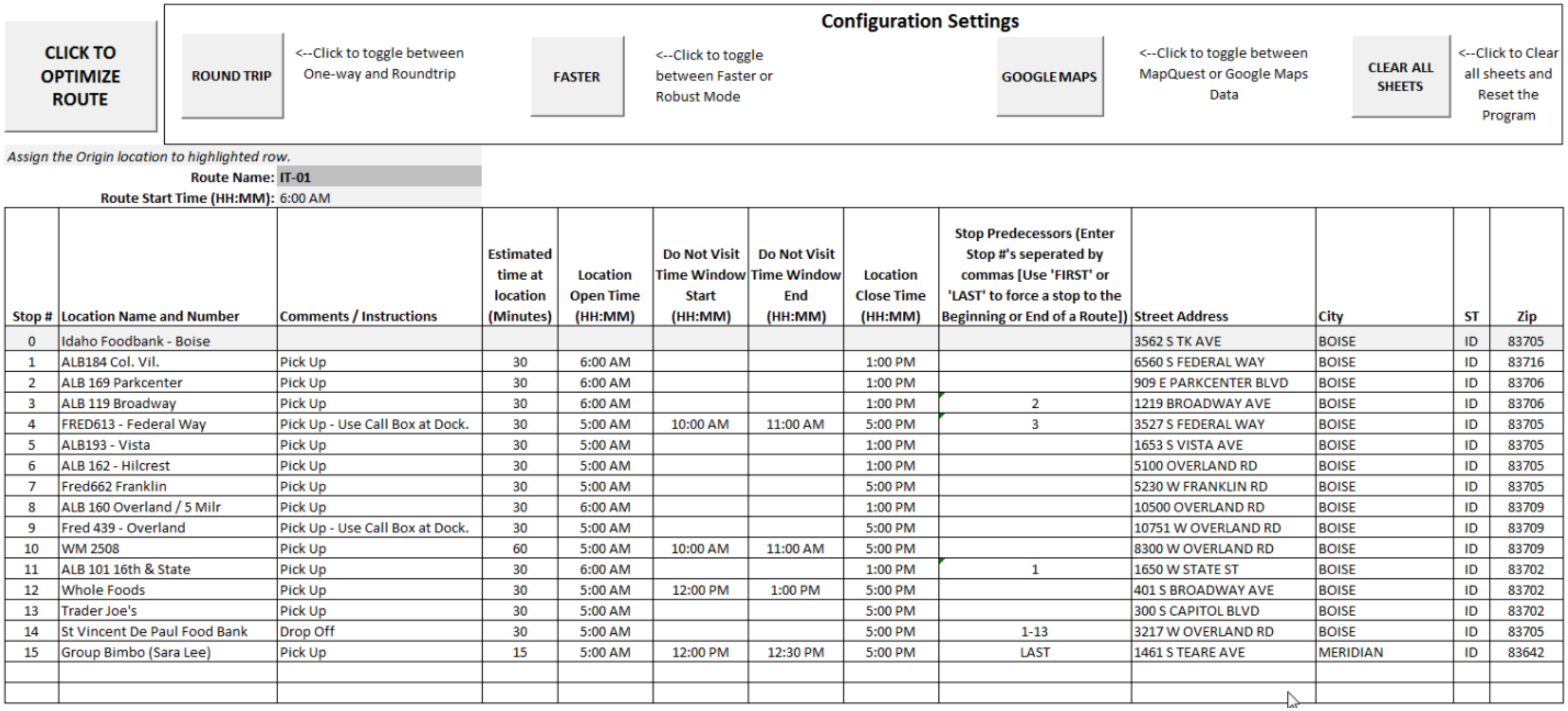


Fig. 1: Architecture of the Route Optimization System.



Stop #	Location Name and Number	Comments / Instructions	Estimated time at location (Minutes)	Location Open Time (HH:MM)	Do Not Visit Time Window Start (HH:MM)	Do Not Visit Time Window End (HH:MM)	Location Close Time (HH:MM)	Stop Predecessors (Enter Stop #'s seperated by commas [Use 'FIRST' or 'LAST' to force a stop to the Beginning or End of a Route])	Street Address	City	ST	Zip
0	Idaho Foodbank - Boise								3562 S TK AVE	BOISE	ID	83705
1	ALB184 Col. Vil.	Pick Up	30	6:00 AM			1:00 PM		6560 S FEDERAL WAY	BOISE	ID	83716
2	ALB 169 Parkcenter	Pick Up	30	6:00 AM			1:00 PM		909 E PARKCENTER BLVD	BOISE	ID	83706
3	ALB 119 Broadway	Pick Up	30	6:00 AM			1:00 PM	2	1219 BROADWAY AVE	BOISE	ID	83706
4	FRED613 - Federal Way	Pick Up - Use Call Box at Dock.	30	5:00 AM	10:00 AM	11:00 AM	5:00 PM	3	3527 S FEDERAL WAY	BOISE	ID	83705
5	ALB193 - Vista	Pick Up	30	5:00 AM			1:00 PM		1653 S VISTA AVE	BOISE	ID	83705
6	ALB 162 - Hilcrest	Pick Up	30	5:00 AM			1:00 PM		5100 OVERLAND RD	BOISE	ID	83705
7	Fred662 Franklin	Pick Up	30	5:00 AM			5:00 PM		5230 W FRANKLIN RD	BOISE	ID	83705
8	ALB 160 Overland / 5 Milr	Pick Up	30	6:00 AM			1:00 PM		10500 OVERLAND RD	BOISE	ID	83709
9	Fred 439 - Overland	Pick Up - Use Call Box at Dock.	30	5:00 AM			5:00 PM		10751 W OVERLAND RD	BOISE	ID	83709
10	WM 2508	Pick Up	60	5:00 AM	10:00 AM	11:00 AM	5:00 PM		8300 W OVERLAND RD	BOISE	ID	83709
11	ALB 101 16th & State	Pick Up	30	6:00 AM			1:00 PM	1	1650 W STATE ST	BOISE	ID	83702
12	Whole Foods	Pick Up	30	5:00 AM	12:00 PM	1:00 PM	5:00 PM		401 S BROADWAY AVE	BOISE	ID	83702
13	Trader Joe's	Pick Up	30	5:00 AM			5:00 PM		300 S CAPITOL BLVD	BOISE	ID	83702
14	St Vincent De Paul Food Bank	Drop Off	30	5:00 AM			5:00 PM	1-13	3217 W OVERLAND RD	BOISE	ID	83705
15	Group Bimbo (Sara Lee)	Pick Up	15	5:00 AM	12:00 PM	12:30 PM	5:00 PM	LAST	1461 S TEARE AVE	MERIDIAN	ID	83642

Fig. 2: The data input and tool configuration user interface in Excel.

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ROUTE NAME: IT-01	Total route time of 3 hours and 26 minutes. Total driving time of 1 hours and 24 minutes.	
	---------- T U R N B Y T U R N D I R E C T I O N S ----------	
Leave origin: 3562 S TK AVE at 6:00 AM		
	Start out going north on S Tk Ave toward W Wright St.	Drive 0.2 miles
	Turn left onto S Federal Way.	Drive 0.2 miles
	Merge onto S Broadway Ave/US-20 E/US-26 E via the ramp on the left.	Drive 0.6 miles
	Merge onto I-84 W/US-30 W toward Nampa.	Drive 4.4 miles
	Merge onto S Cole Rd via EXIT 50A toward Overland Rd.	Drive 0.4 miles
	Turn right onto W Overland Rd.	Drive 2.1 miles
Drive 11.4 minutes to arrive at STOP: ALB 160 Overland / 5 Milr [10500 OVERLAND RD] at 6:11 AM		
* Spend 5 minutes at location (until 6:35 AM)	<> Arriving before this stop opens at 6:30 AM. Wait for 19 minutes. <>	
	--> Leave this stop at 6:35 AM	
	Start out going east on W Overland Rd toward S Five Mile Rd.	Drive 1.6 miles
Drive 3 minutes to arrive at STOP: WM 2508 [8300 W OVERLAND RD] at 6:38 AM		
* Spend 5 minutes at location (until 6:43 AM)		
	--> Leave this stop at 6:43 AM	
	Start out going east on W Overland Rd toward Penninger Dr.	Drive 1.5 miles

Fig. 3: Sample route output with turn by turn directions and instructions for the driver.