The Missouri Lottery Optimizes Its Scheduling and Routing to Improve Efficiency and Balance

Wooseung Jang, Huay H. Lim, Thomas J. Crowe

Department of Industrial and Manufacturing Systems Engineering, University of Missouri–Columbia,
Columbia, Missouri 65211 {jangw@missouri.edu, hhl38b@mizzou.edu, crowet@missouri.edu}

Gail Raskin, Thomas E. Perkins

The Missouri Lottery, 1823 Southridge Drive, Jefferson City, Missouri 65109
{raskig@molottery.com, perkit@molottery.com}

The Missouri lottery, a profit-driven nonprofit organization, generates annual revenues of over $800 million by selling lottery tickets; 27.5 percent of the revenue goes to Missouri's public education programs. The lottery sales representatives (LSRs) play a central role in increasing sales by providing excellent customer service to ticket retailers throughout the state. Hence, LSRs must have equitable, balanced work schedules and efficient routes and navigation sequences. Our objective was to provide scheduling and routing policies that minimize LSRs' total travel distance while balancing their workloads and meeting visitation constraints. We modeled the problem as a periodic traveling-salesman problem and developed improvement algorithms specifically to solve this problem. The newly implemented schedules and routes decrease the LSRs' travel distance by 15 percent, improve visitation feasibility by 46 percent, increase the balance of routes by 63 percent, decrease overtime days by 32 percent, and indirectly increase the sales of lottery tickets by improving customer service.

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The Missouri lottery operates as a state agency under the state's department of revenue. State statutes and the legislature restrict and monitor it as a nonprofit state agency. However, the Missouri lottery's business is to produce revenue by selling tickets and to bring profit to the state education fund. Hence, it is characterized as a profit-driven nonprofit organization. Its goals are to provide good quality service to the public and to increase revenue and profit at a minimal cost.

The Missouri lottery's profits have risen steadily, and the lottery has produced more than $2.2 billion for the state since it was established in 1986. During fiscal year 2004, it transferred $230.3 million to elementary, secondary, and higher education. Of every dollar that goes into a lottery game, 60.5 cents are paid out in prizes, about 27.5 cents are later spent on education, and the remaining 12 cents go for administrative costs and incentives for retailers. Proceeds from the lottery represent about three percent of state spending on elementary, secondary, and higher education in Missouri (*Columbia Daily Tribune* 2004). The lottery increased revenues by increasing jackpot amounts, introducing new games, and making innovations. The Missouri lottery recognizes the importance of these initiatives and is always seeking ways to streamline its operation.

The Missouri lottery comprises five divisions: Executive, Marketing, Finance and Administration, Communication, and Security. The marketing division provides service to lottery ticket retailers and handles procurement and sales promotions. The lottery sales representatives (LSRs) and the tell-sell marketing representatives (TMRs) serve and manage retailers. The LSRs are external agents, visiting retailers and meeting their requirements. The TMRs are internal agents who make and receive calls concerning ticket orders and requests. These two teams of representatives increase sales by providing quality service to ticket retailers.

Because of their importance, the LSRs need equitable and balanced work schedules and efficient

routes and visiting sequences. The policy for scheduling and routing the LSRs had never been scientifically evaluated. The Missouri lottery contacted those of us from the university in 2002 to develop efficient solutions to its LSR scheduling and routing problems. Our goal was to minimize the LSRs' total travel distance while balancing their workloads and satisfying visitation constraints. To develop and implement such a policy, we relied on close collaboration between the research team and the Missouri lottery. The lottery appointed a project committee, consisting of the director of marketing, the re-operation manager, the research and development manager, the sales managers, several LSRs, and other sales and marketing personnel. This committee was actively involved throughout the project.

Problem Description

The Missouri lottery headquarters are in Jefferson City, and it has regional offices in Springfield, Kansas City, and St. Louis. Each of four regions has a regional sales manager and several district sales managers, who oversee office operations and supervise the LSRs. The number of LSRs in each region depends on the number and size of ticket retailers. The sales managers and LSRs review and arrange the LSRs' service routes to ensure balance and efficiency.

The Missouri lottery employs 39 LSRs statewide to cover more than 5,000 ticket retailers. In our analysis, the exact number was 5,043, although the number changes frequently. Each sales representative is assigned about 130 retailers in a given geographical region. Assignments are usually divided by county in rural areas and by major streets or highways in urban areas, such as St. Louis and Kansas City. The representatives generally visit the ticket retailers once every other week, although they visit those with very high sales volumes every week. During each visit, the LSR checks on product inventory, replenishes supplies and ticket stock, collects returned tickets, presents statewide promotions, contacts decision makers, cleans the point-of-sale counters, inspects game equipment (such as instant ticket-vending machines, online terminals, and Keno machines), and files administrative forms (Figure 1).

The LSRs are categorized as local or remote. The local LSRs work from the office; the remote LSRs
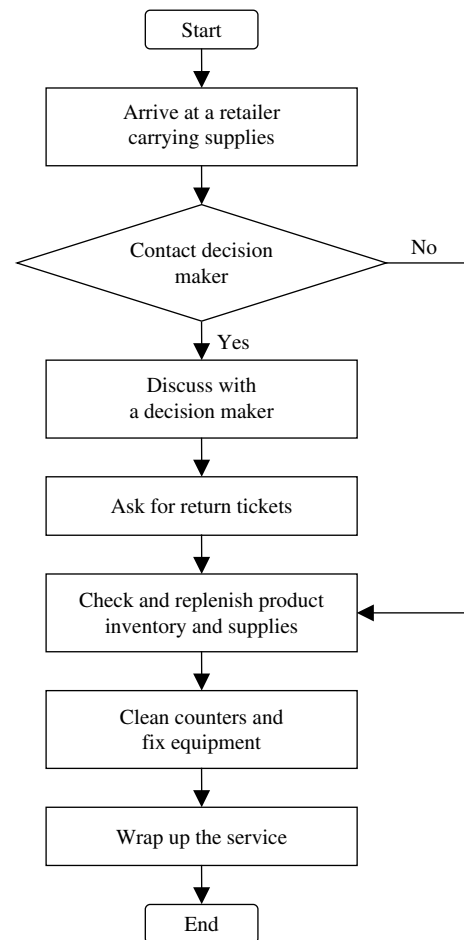
Figure 1: The lottery sales representative's (LSR's) routine business processes in visiting retailers include checking on product inventory, replenishing supplies and ticket stock, collecting returned tickets, presenting statewide promotions, contacting decision makers, cleaning the point-of-sale counters, inspecting game equipment, and filing administrative forms.

start their routes from their homes. All LSRs attend a regular meeting every other week scheduled by the regional office to learn about new games and promotions and to discuss administrative issues. The remote LSRs usually take the opportunity to pick up enough point-of-sale items from the warehouse to last them until the next regular meeting.

Initially we designed efficient and balanced routes for the LSRs without changing their assigned retailers. By reassigning retailers, we could have achieved greater efficiency, but upper management was reluctant to sanction such a drastic change. Many LSRs

have served the same retailers for over 10 years. Changing retailer assignments could jeopardize close and longstanding relationships with managers and owners and compromise service quality. It would also complicate the implementation of our results and cause the LSRs to resist route changes. Therefore, we took a gradual approach, improving the routes of the LSRs in their existing territories.

We had multiple objectives. The most important one was to decrease mileage and thereby the costs of operating the LSRs' vans, the LSRs' driving times, and possibly the number of LSRs.

The second objective was to balance the LSRs' routes. Many LSRs work as much as 12 hours on some days because they would rather cover a certain geographical area in one trip than in several. This behavior does not increase the lottery's cost because all LSRs are salaried. However, the managers believe that the LSRs' working such long hours provide inferior service.

The third objective was to insure that routes conform to retailers' time windows. Some ticket retailers ask the LSRs to visit at certain times. For example, some bars and clubs open in the afternoons, so the LSRs cannot schedule visits in the mornings. Other stores and restaurants want the LSRs to avoid their peak operating times, usually lunch hours. Some owners and managers of stores want the LSRs to visit when they are available so they can handle the lottery tickets. Although it is preferable to respect such time constraints, they are not inviolable.

Unfortunately, these objectives sometimes conflict. For example, balancing route times may cause inefficiencies because the LSRs should return home after about eight working hours even if the next retailer to visit is very close to the last stop of the day. Visiting that retailer the following day incurs additional driving time, which means inefficiency. The challenge comes in coordinating these three important, possibly incompatible objectives: efficiency, balance, and feasibility.

Related Work

Our problem is closely related to other practical routing and scheduling problems. Waste Management, which provides waste-collection services,

developed a comprehensive route-management system that improved its routing, dispatching, maintenance, and management of its large fleet of vehicles (Sahoo et al. 2005). It used variations of the vehicle-routing problem (VRP) with time windows and additional constraints, mainly to minimize the number of vehicles and travel time. The company expected to save $44 million by reducing the number of collection routes by 10 percent.

Schindler Elevator Corporation, which designs, manufacturers, installs, maintains, and modernizes internal transport systems for almost every type of building, developed an automated route-scheduling and planning system to optimize its technicians' service routes. The system assigned maintenance work to technicians and created efficient day routes by solving the periodic VRP. Using these automated tools, Schindler saved more than $1 million annually and increased managers' awareness of operating revenue (Blakeley et al. 2003).

TransAlta Utilities, Canada's largest publicly owned electric utility company, used facility location and vehicle-routing heuristics to establish call centers and redesign its service-delivery network (Erkut et al. 2000).

Weigel and Cao (1999) developed algorithms for the VRP with time-window constraints to solve Sears' technician-dispatch and delivery-schedule problem. A solution minimizing an objective function, which includes travel time, route duration, a time-window-violation penalty, and waiting time, resulted in more than $9 million in one-time savings and more than $42 million in annual savings.

Adenso-Diaz et al. (1998) applied a hierarchical approach to design and implement a decision-support system to organize the delivery network for the products of a large dairy in Spain. Their objectives were to fairly distribute clients among vendors and to save traveling distance in each vendor's route. They used a traveling-salesman problem (TSP) model with time-window constraints and claimed about 10 percent savings when all their recommendations were implemented.

In 1994, IBM developed a crew-planning-optimization system (CPOS), which US Airways and Southwest Airlines used. In its 1996 annual report, US Airways said CPOS saved the company $50 million

annually (Anbil et al. 1999). In a 1998 IBM press release, Al Davis, vice president of special projects at Southwest Airlines, said "CPOS generates daily, weekend and transition pairing solutions in a fraction of that time, while reducing aircraft ground time, crew work hours, flight schedule costs and, more importantly, improving quality of life for airline crews and schedulers."

Even small companies are taking advantage of scientific and competent scheduling systems. Martin (1998) studied the efficiency of product distribution for a centralized bakery. He claimed that the cost saving from minimizing routes was insignificant but meeting delivery times at low cost affected profit significantly. He used a simulation process to validate new routes.

Begur et al. (1997) developed a spatial decision-support system to schedule available nurses to go to patients' homes and determine their travel routes. They used the TSP solution based on the Clarke and Wright's (1964) savings-type route-building heuristic. After minimizing the total travel time, the estimated savings were more than $20,000 per year in travel expenses, paperwork time and cost, and nursing personnel requirements.

Weintraub et al. (1996) developed an operative and computerized system based on a simulation process with heuristic rules to support daily truck scheduling and routing decisions in the forest industry. They claimed that many firms reduced their total transportation costs by as much as 20 percent.

The application of new thinking is not limited to commercial companies. In 1990, North Carolina's department of public instruction spent over $147 million and used more than 13,000 yellow buses to transport students to and from school. By modifying bus routes and schedules and reducing the number of buses, the state saved approximately $7 million annually in operating costs (Sexton et al. 1994).

The scheduling and routing problem we considered theoretically belongs to the periodic-traveling-salesman problem (PTSP) category in the operations research literature. It is a generalization of the well-known TSP and is a difficult optimization problem. (Gutin and Punnen 2002, Lawler et al. 1985 review the TSP.) In the classical TSP, a salesman starts from a home city, visits each customer exactly once, and returns home. The planning period is usually one day, so one needs to create a minimum cost cycle for customers who must be visited on that day. The PTSP extends the planning period to M days. Over the M-day period, each customer must be visited at least once; some customers require several visits. The objective is usually to minimize travel distance or time while satisfying certain time and visit constraints. Unlike the classical TSP, the PTSP is the subject of few published results. Christofides and Beasley (1984) originally proposed a heuristic for the PTSP with an explicitly specified set of visit-day combinations for each city. Chao et al. (1995) and Paletta (1992, 2002) also considered the PTSP and presented improved heuristic algorithms. Because of the complexity and size of the problem, obtaining an optimal solution is often impractical or impossible. Hence, researchers commonly use various heuristics to find reasonably good solutions within acceptable computational times. In our project, we developed several improvement algorithms specifically for our problem by modifying known heuristics.

Although our project overlaps others in some respects, it includes several unique and interesting features and results. Applications of the TSP and the VRP have been among the great success stories of operations research; however, most of the successes occurred at for-profit commercial companies. Our application problem occurred in a nonprofit state-government agency. The mathematical model of our project is also a little-investigated PTSP problem, and we particularly emphasized balance among routes and route distance in an objective function; typical applications focus on route minimization possibly with time-related constraints.

Data Collection

We conducted two surveys and several interviews to get input from the sales force before diving into detailed analysis. We collected and analyzed three major categories of data. The first category was the specific information about retailers. The existing Missouri lottery database contained such basic information as retailers' addresses, telephone numbers, latitude and longitude, store types, accounting and billing options, types of games sold, types of

machines used for games, and sales volumes. We needed more information for our analysis.

In the first survey, we obtained information about service times during LSR visits and the time-related constraints for each retailer. The survey results showed that LSRs spent an average of 19.6 minutes at a retailer. The LSRs responded that 94.4 percent of their visits took between 10 and 30 minutes, while the remaining 5.6 percent took more than 30 minutes. Most LSRs stated that the longer stops were associated with equipment problems, billing adjustments, ticket returns, special ticket orders, and new accounts. The LSRs also rated different factors' effect on their service times. Among these factors, types of games sold and sales volume significantly affected service times. Based on the results of the survey, we categorized ticket retailers and estimated the average service time for each group, with the total average time being 20 minutes. We later confirmed our estimates in our rides and visits with the LSRs. In this survey, the LSRs also listed any visitation time windows associated with various retailers.

We obtained a set of data on driving distances and times between retailers. We used commercial mapping software after transferring location information from the lottery database to determine these values. While the driving distance is straightforward, the driving time depends on the driver and on traffic conditions. We first computed street-based travel distance and time, assuming that the driving speed was the local speed limit. Then, we adjusted the travel time to 120 percent of that time in rural areas and 150 percent in urban areas, to account for slow drivers and city traffic.

Our third set of data concerns the LSRs' current working schedules and routes. In our second survey, we asked the LSRs to record their daily activities for a two-week period. They provided us with office time, traveling time, starting and ending times of each day, and location information, such as their starting and ending places, and exact sequence of visits to retailers. We used this information to design our solution. We wanted to preserve as many of the LSRs' activities as possible so that the implementation of new routes would be minimally inconvenient and complicated. We used these original routes as an initial solution in our program.

Analysis and Solution Procedure

After collecting the data, we compiled it to fit the structured format required by our main analysis program and to make it easy to update. Our data-analysis program performs this process automatically. At the end of the analysis, we used commercial map software as a graphical tool to illustrate the outcome of our analysis. It generates new routes and time-specific schedules for the LSRs (Figure 2).

Our algorithm determines the daily routes for a biweekly (10 day) planning period by simultaneously finding the best allocation of retailers over the period and the best visiting sequence within each daily route. Suppose that an LSR must visit n retailers
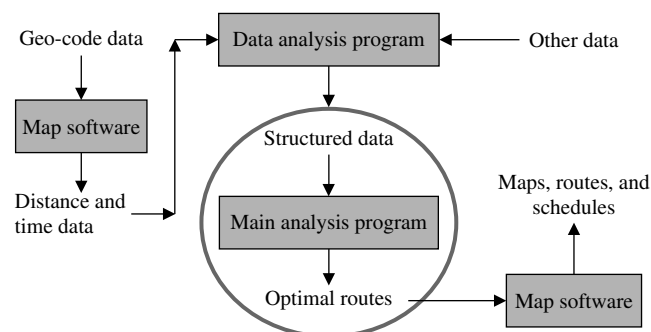
Figure 2: In the automated scheduling and routing system we developed, the commercial mapping software computes street-based travel distances and times at the beginning and creates graphical routes and time-specific schedules at the end. Our data-analysis program compiles data to fit a structured format that is easy to use and update. Our main analysis program uses several improvement heuristics specifically developed for the problem.

during the 10-day period. We use the following attributes:

t: designation of the day in the planning period, $t = 1, 2, \ldots, 10$.

i, j: designation of the retailer, $i, j = 1, 2, \ldots, n$.

d_{ij}: travel distance from retailer i to retailer j.

c_{ij}: travel time from retailer i to retailer j.

s_i: service time required for retailer i.

l_i, u_i: earliest and latest arrival times at retailer i.

The LSR should be at retailer i between l_i and u_i, but a violation is acceptable. Subscript 0 represents a depot (home or office) for the route.

We use a set of decision variables x_{ijt}, which has the value 1 if the LSR travels from retailer i to retailer j on day t, and 0 otherwise. The travel distance of the LSR on day t, D_t, is

$$D_t = \sum_{i=0}^{n} \sum_{j=0}^{n} d_{ij} x_{ijt}.$$

Because the LSR's travel time and service time on day t are

$$\sum_{i=0}^{n} \sum_{j=0}^{n} c_{ij} x_{ijt} \quad \text{and} \quad \sum_{i=0}^{n} \sum_{j=0}^{n} s_i x_{ijt},$$

respectively, the LSR's total working time on day t, C_t, is

$$C_t = \sum_{i=0}^{n} \sum_{j=0}^{n} (c_{ij} + s_i) x_{ijt}.$$

The lottery management would like the LSRs to work similar hours every day, that is, balanced routes. Working eight hours one day and seven hours another day is better than working nine hours one day and six hours the next. To measure the balance of individual routes, we derived a balance metric using the mean square deviation, which measures the squared difference between the length of individual routes and the average route length for each LSR as follows:

$$\text{balance metric} = \sum_{t=1}^{10} (C_t - \bar{C})^2,$$

where $\bar{C} = \sum_{t=1}^{10} C_t / 10$.

We use a weighted objective function composed of a term for minimizing travel distance and a term

for penalizing imbalanced routes. Hence, the objective function becomes

$$K(x_{ijt}) = w_1 \sum_{t=1}^{10} D_t + w_2 \sum_{t=1}^{10} (C_t - \bar{C})^2, \tag{1}$$

where w_1 and w_2 are weights used to adjust the importance of different factors.

The workday without overtime is easily determined using C_t such that

$$C_t \leq 8. \tag{2}$$

On days when the regional office holds the LSR's biweekly meetings, the workday is limited to five hours, such that $C_t \leq 5$. Let $[k]$ be the kth retailer the LSR visits during day t. Suppose that $[k] = j$. That is, retailer j is the kth retailer in the LSR's visitation sequence on day t. The values of $[k]$ can be computed easily from the values of x_{ijt}. Then, the arrival time of the LSR at retailer j is $\sum_{i=0}^{k-1} (c_{[i][i+1]} + s_{[i]})$, and the time-window constraint for retailer j becomes

$$l_j \leq \sum_{i=0}^{k-1} (c_{[i][i+1]} + s_{[i]}) \leq u_j. \tag{3}$$

Our objective is to minimize the value in (1) and simultaneously to increase the number of days satisfying Equation (2) and the number of retailers satisfying Equation (3). These objectives may conflict, so we need to balance them, not just simply minimize the objective function. Because our problem is complex, we used a heuristic technique.

We used the LSR's old schedules and routes as initial routes and chose only improved solutions that satisfied certain criteria in our analysis. However, in the absence of existing routes, we would need to create initial routes to transfer our method to other settings and to obtain different final solutions, whose qualities depend on the initial routes.

We could use many heuristic algorithms to construct initial 10 routes for each LSR, but we tried a cluster-first, route-second type algorithm similar to Fisher and Jaikumar's (1981). The algorithm starts with 10 seed retailers and expands routes by inserting nearest retailers. The seed retailers chosen affect the quality of the initial routes, which, in turn, determines the quality of the final solution. In our analysis, we manually selected seed locations in consultation

with managers and the LSRs, who are familiar with retailer locations. However, we could have selected seed locations randomly or systematically. For example, Fisher and Jaikumar claimed that customers often lie along radial corridors corresponding to major thoroughfares; hence, the most distant customers along these corridors are natural seed customers. After we decide on the seed locations, we select the nearest unassigned retailer and assign it to a route without violating the time constraint (2). If we can assign all the retailers without violating the constraint, we have our initial 10 routes, which require no overtime work. Even if we cannot avoid the violation, we continue assigning retailers to routes, in the expectation that we will improve the routes later through the following improvement algorithms:

—The interroute-improvement heuristic iteratively transfers retailers from one route to another or exchanges retailers between two different routes. It proceeds by choosing a subset of retailers and enumerating the possible combinations of visits for this subset, seeking an improved solution.

—The intraroute-improvement heuristic applies a local optimization technique to each route separately to improve the objective function value of the route. It uses Lin's (1965) well-known 2-opt edge-exchange heuristic.

—Our algorithm accepts new solutions generated by interroute-improvement or intraroute-improvement heuristics if they decrease the objective function value (1) without increasing the number of days and retailers violating (2) or (3). Even though the new solution increases the objective function value (1), it is also accepted if the increase is less than α and if it increases the number of days and retailers satisfying (2) or (3). In other words, the algorithm accepts a worse solution if it mitigates certain constraints. It also helps us find a globally optimal solution getting out of the local optima.

Our algorithm repeats the interroute- and intraroute-improvement heuristics until no new solution satisfies the given acceptance criteria. When it is finished, it creates a daily route for each of the planning periods. By adjusting the values of w_1, w_2, and α, we can generate a variety of policies with different characteristics and select the one that best fits the given situation.

There are multiple ways to adjust the values of the parameters. The systematic method we used was to iteratively increase the values of w_2 and α while maintaining $w_1 = 1$. At the beginning, we set $w_2 = \alpha = 0$. That is, we solve a typical TSP with a distance minimization objective. Then, we try to find alternative solutions as we increase the value of w_2. In other words, we investigate solutions with more balanced routes but potentially with longer driving distances. We repeat the process with increased values of α, which is specified as a percentage of the known best solution during the iteration process, starting from one percent. For example, if the known best solution has the distance x, we select a new solution with a distance less than $(1 + \alpha)x$, which can be worse than the known best solution as long as it satisfies more constraints. That is, we look for solutions satisfying more constraints at the expense of efficiency.

We repeat the algorithm until we identify several potential solutions. The managers at the Missouri lottery along with the researchers determine a final solution that has good efficiency and balance after inspecting quantitative measures, such as driving mileage, balance, and constraint violation, and qualitative information, such as routing maps.

Implementation Issues

As is common, we had some problems during implementation. We had to deal with unexpected issues and modify our results so they could be successfully implemented. Despite careful planning and data collection, we discovered many errors in the retailers' geographic information in the lottery database and in the survey data. Correcting them took a lot of time.

After modifying the necessary information, we distributed our new results to managers and the LSRs to elicit their feedback. Many LSRs liked their new routes from the beginning; several suggested further changes. They often based these suggestions on their experiences and human considerations, which our analysis could not capture. For example, they mentioned traffic congestion in some areas on Friday afternoons, the difficulty of making left turns at certain intersections, dangerous highway exits, and neighborhoods that were unsafe late in the afternoon. Managers also wanted good-looking routes with better clusters of retailers and less overlapping and cross
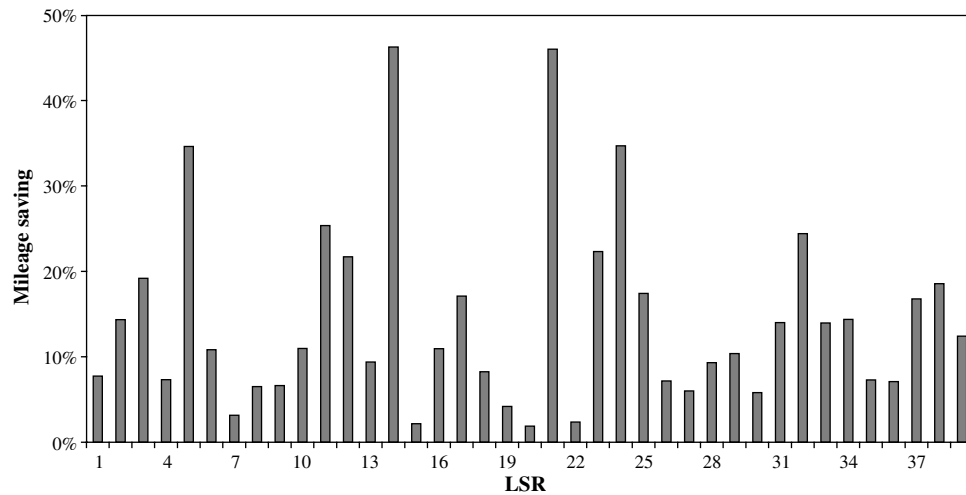
Figure 3: The new scheduling and routing policy results in an average saving of about 15 percent per lottery sales representative (LSR). It saved less than 10 percent for 17 LSRs, between 10 and 20 percent for 14 LSRs, and more than 20 percent for eight LSRs.

over between routes. The visual attractiveness of a solution, which depends on how stops are grouped in a route, is an important criterion in many practical routing applications (Kim and Kim 2003, Poot et al. 1999). Based on managers' and the LSRs' suggestions, we modified many routes even when changes came at the expense of efficiency. These changes definitely facilitated implementation. The LSRs were excited to have new routes that they and we liked, and they were likely to use them.

Cost Saving and Benefits

Our primary objective in this project was to decrease the LSR's driving distance and time. The other criteria were feasibility of routes, balanced working hours, and a decrease in overtime days. The routes we obtained are superior to the old routes in all of these respects.

Our results are based on our analysis of the 39 statewide LSRs. Their total driving distance based on the old routes was 34,564 miles every two weeks. The new schedule has a driving distance of 29,374 miles. Thus, the new policy saves 5,190 miles every two weeks, an average saving of about 15 percent per LSR. The largest individual saving was 46 percent; the smallest was two percent. Several LSRs had been using very efficient routes. We saved less than

10 percent for 17 LSRs, between 10 and 20 percent for 14 LSRs, and more than 20 percent for eight LSRs (Figure 3).

According to the study of Crowe et al. (2000) on the operation of the Missouri lottery, the procurement cost of LSR vans is 18.7 cents per mile and the cost of gas is 10.2 cents per mile, based on their calculation of 17.66 miles per gallon and the prevailing gas price of $1.80 per gallon in 2004. If we add the average vehicle-maintenance cost of 6.1 cents per mile (AAA Midwest Traveler 2004), the total operation cost of LSR vans is 35 cents per mile. Because our improvement is equal to an annual saving of 134,940 driving miles, the total cost saving from the decreased driving mileage is approximately $47,229 per year.

The new policy also decreases LSRs' traveling hours from 921 to 789 for the two-week period. This saving is equal to 1.65 LSR-hours, assuming 40 working hours per week. The value of annual saving would be $51,419 based on the LSR's average annual salary of $31,163, although the lottery does not save this amount while it maintains 39 LSRs. However, the LSRs can now spend the time recruiting new ticket retailers and handling additional documentary work, which they previously could not do because of their tight work schedules.

In addition to these direct cost savings, the new routes provide other benefits, whose monetary values
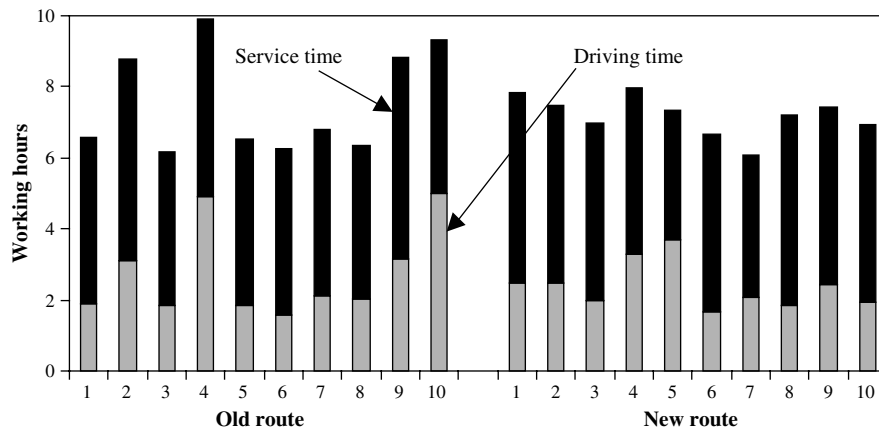
Figure 4: In this example of time analysis of the LSR's routes, the left half of the figure represents an LSR's former biweekly routes and the right portion is the new routes. The bars are divided into driving times (bottom) and service times (top). This LSR used to drive 1,102 miles and now drives 945 miles biweekly, a 14.2 percent decrease saving 3.58 hours. Moreover, the new routes provide a much more balanced schedule. The LSR worked over eight hours on four days under the old schedule, but now can finish every route within eight hours.

are somewhat difficult to quantify. While the old routes violated 162 time-window constraints, the new schedule has only 87 violations, a 46-percent feasibility improvement. This improvement directly affects the quality of customer services and increases customer satisfaction, which indirectly affects the ticket sales. The violations of time-window constraints expressed as a percentage of the total number of retailers was 3.2 percent (162 violations out of 5,043 retailers), which does not seem to be a prevalent problem. However, if we consider only the 427 retailers, who originally had time-window constraints, the percentage of violations was 38 percent (162 violations out of 427 retailers) and is now 20 percent (87 violations out of 427 retailers) using the new routes.

We measured the balance of individual routes using the new balance metric. The sum of the balance metric values for all LSRs has decreased from 1,103 to 410, a 63 percent enhancement (Figure 4). Another way to identify the balance of routes is to count days of overtime. The old schedule had 113 routes that required the LSRs to work more than eight hours, including both driving and service times. The new schedule has 77 such routes, representing a 32 percent improvement. Overtime is a prevalent problem. The percentage of the LSRs' overtime days was 29 percent (113 routes out of 390 routes) and is still 20 percent (77 routes out of 390 routes) after implementing

better routes. However, the new schedule decreases the number of very long work days, dropping days with more than nine working hours from 55 to 18, a 67 percent improvement and days with more than 10 working hours from 39 to 4, a 90 percent improvement. The more balanced routes should improve the quality of LSR service to ticket retailers.

We plotted retailers using latitude and longitude and constructed routes by linking retailers with straight lines instead of with street-based connections (Figure 5). One important and unique result of our analysis is the list of direct comparisons between old and new routes by the LSRs. This list offers practitioners interested in employing an optimized routing system a guideline to estimate the potential cost saving in their operations. On the other hand, the authors of almost all the published work just aggregated cost savings in dollar terms. These figures are important but not very useful for computing estimated benefits in other companies. Moreover, we explicitly compare optimal routes with actually implemented routes after considering feedback from the Missouri lottery.

Extension—Retailer Reassignment

The Missouri lottery managers wanted to maintain the number of LSRs and the retailers assigned to them during the project to avoid disrupting their operations. However, the successful implementation of our
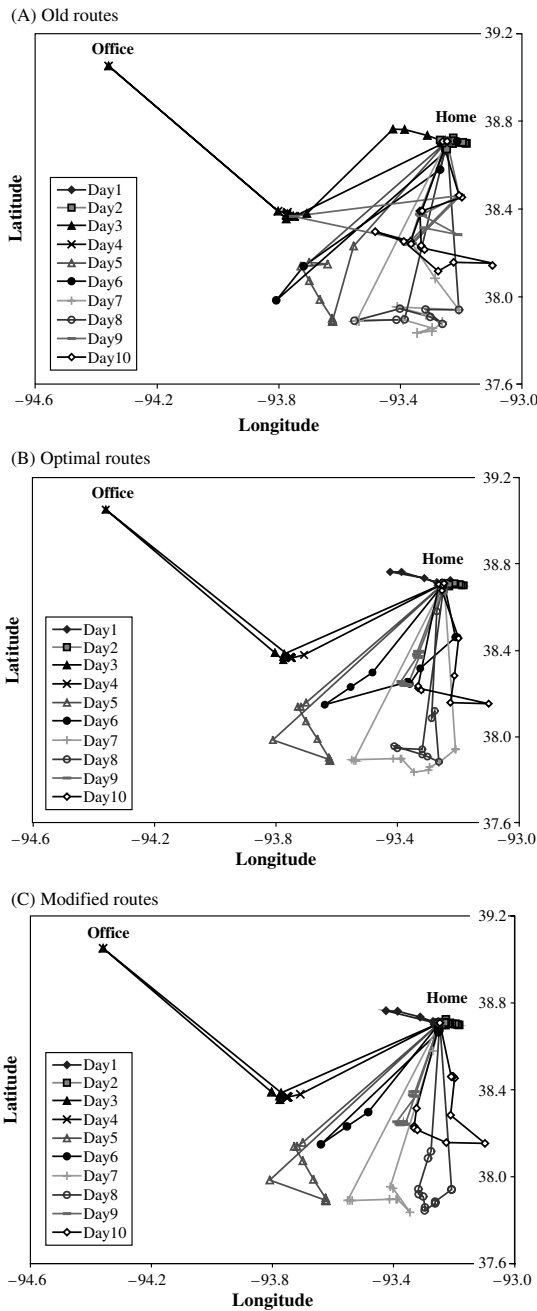
Figure 5: Map A represents a lottery sales representative's (LSR's) old routes, several of which are inefficient and overlapping. This LSR drove 1,432 miles on these routes in two weeks. Map B shows the routes the research team originally proposed. Although they include some crossovers and overlaps, the routes are very efficient, with only 1,022 driving miles, a 28.6 percent reduction. Map C represents the final routes after we modified the optimal routes based on feedback from the LSR and sales managers. The final routes are visually attractive with good clusters of retailers. However, they require 1,112 driving miles, only a 22.3 percent improvement over the old routes.

results gave them confidence to make more radical changes to improve efficiency. We are developing LSR routes for different numbers of LSRs with new retailer assignments. We are using clustering and assignment algorithms to assign retailers to the LSRs. Once we finish assigning retailers, we can develop new routes using our existing algorithms.

The essence of our reassignment problem is to partition a set of retailers into p mutually exclusive and collectively exhausting groups, restricting the size of each group based on estimated driving and service times. We use a variation of the capacitated clustering algorithm to create regions or clusters of retailers. The capacitated clustering problem belongs to an NP category, and many clustering and location heuristics depend on local improvements and greedy algorithms. Our heuristic also uses algorithms similar to MacQueen's (1967) p-means algorithm and the primal heuristic developed by Mulvey and Beck (1984) and Koskosidis and Powell (1992).

We start with a set of p starting medians, which include home or office locations of the LSRs and some manually selected locations. We try to assign retailers to their nearest median without violating a cluster capacity, which we determine by combining the driving and service times of the retailers in the cluster. Retailers are assigned in decreasing order of regret, the absolute value of the difference between the retailer's first and second nearest medians (Mulvey and Beck 1984). The retailer with the largest regret value is assigned first to minimize the potential penalty of inappropriate assignment.

When the assignments are completed, we build 10 routes using the initial route-construction method and record the driving distances for servicing the retailers in each cluster. We repeat this procedure using new medians, which minimize the sum of distances between them and all other cluster members, to see whether clusters based on new medians can decrease the LSRs' total driving distances. We continue the iteration until there is either no change in the median set or no saving in the driving distance.

Next, we try to improve the solution by transferring and exchanging retailers among clusters. At this stage, we try to improve the total driving distances and balance the workload among the LSRs. We complete the retailer-assignment procedure after making

all feasible transfers and exchanges. We obtain the final LSR routes by applying the route-improvement algorithms to each cluster independently.

Conclusion and Future Direction

As a result of our project, the Missouri lottery saves costs by improving its LSR operations. Balanced scheduling and efficient routing of the LSRs keep costs down and morale up. Furthermore, they improve customer service and satisfaction, both of which contribute to increased lottery ticket sales. Although we cannot measure the effect exactly, we believe that the implementation of our project has increased ticket sales. The Missouri lottery's revenue is growing steadily: the profit during fiscal year 2004 was $230.3 million, a 19 percent increase from the previous year's $193.3 million (*Columbia Daily Tribune* 2004). Although larger Powerball jackpots and the introduction of new games are the main causes of the increased revenue, the innovations and improved customer service achieved by the Missouri lottery together with the university research team have also presumably contributed to this increase.

The new system developed through this project also provides noneconomic benefits. It can update the routes quickly when current retailers leave or move, and when new ones arrive. The sales staff takes less time to reallocate retailers, perform updates, and monitor routes than it did in the past. Also, this computer-based system takes more factors into consideration and it handles complex scheduling policies that the former system could not. The managers can now confidently plan LSR scheduling and routing. The optimization engine enables them to tackle the toughest schedules and gives them the confidence to convince others. The Missouri lottery, together with the researchers, plans to develop graphical user interfaces for the automated scheduling and routing system, which will allow its managers to use the system independently.

Thanks to the success of this project, the Missouri lottery is considering the development of further advanced LSR scheduling and routing models. Specifically, we plan to stratify retailers into groups and assign each group a different visitation frequency, ranging from once a month to several times a week.

This reassignment will increase service quality to the most important ticket retailers without increasing the LSRs' overall workloads. In stratifying retailers, we will have to change some retailers' assignments to the LSRs, thereby making the scheduling and routing policy even more efficient.

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Larry P. Jansen, Executive Director, Missouri Lottery, 1823 Southridge Drive, PO Box 1603, Jefferson City, Missouri 65102-1603, writes: "I am writing this letter to verify Dr. Jang and his research team's work submitted to the journal *Interfaces*.

"In 2002, we decided to develop more efficient scheduling and routing strategies for our sales representatives, who have a huge impact on our sales growth by providing best quality customer service to lottery ticket retailers. We formed a project committee and contacted Dr. Jang and the university research team to undertake a project that would eventually provide efficient solutions to our scheduling and routing problems.

"The project was a huge success. Efficient schedules and routes were developed, the implementation was successfully carried out, and the estimated cost saving was realized. The outcome of the project provided not only more efficient routes, but also more balanced routes. They decreased overtime days and satisfied more visitation constraints we had.

"In short, we saw improvement in operation cost, route flexibility, employee morale, decreased time, and customer satisfaction. Thanks to success of this project, we are currently working with Dr. Jang on another project to develop further advanced scheduling and routing models for our sales representatives."