MGT 40750 – Quantitative Decision Modeling
Spring 2017

Network Models
Integer and Nonlinear Programming

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Optimization

- Optimization
  - Linear programming
  - Network models
  - Integer programming
  - Nonlinear programming

Network Models

- **Main Idea**: Efficiently planning and controlling the movement of subjects through the network.
- Examples:
  - Supply Chain: Walmart, Dell, Amazon, FedEx
  - Transportation models
  - Shortest path models

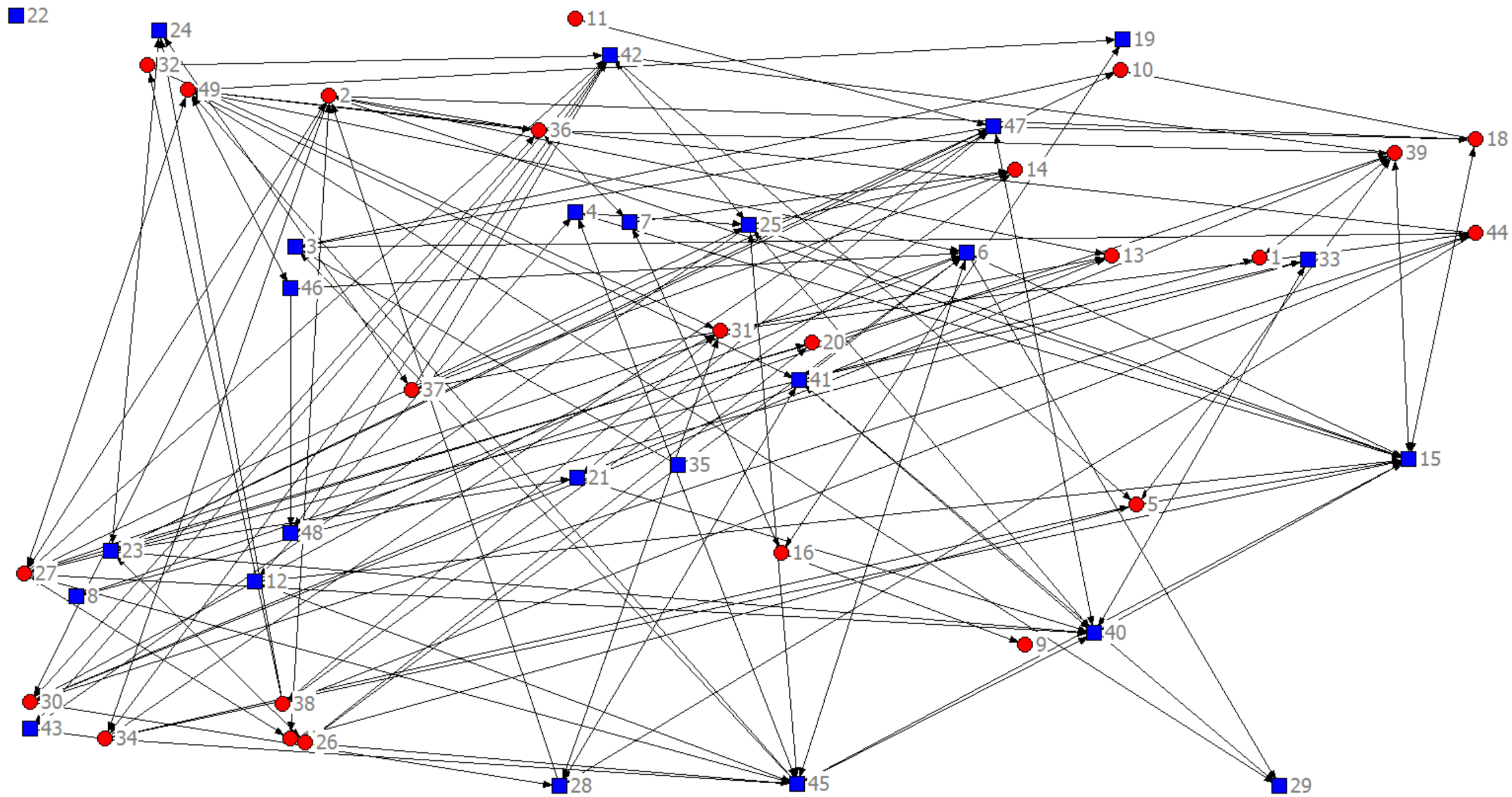
Example: Shortest Path for Messaging

- Consider the mobile social network among students in MGT 40750.
- Question: Find the shortest path between a pair of nodes through this mobile social network.

Example: Shortest Path for Messaging

The mobile social network among students in MGT 40750 is provided in the following diagram, where ● represents Female and ■ represents Male.

Question: Find the shortest path from Node _____ to Node _____ through this mobile social network.



Shortest Path for Messaging

Set up the Shorted Path for Messaging model in Excel: (Start = ___ End = ___)

	A	B	C	D	E	F	G	H	I	J	K	L
1	**Shorted Path for Messaging**											
2												
3	Network Structure											
4	From	To		Flow		Flow balance constraint					Objective to minimize	
5	1	36				Node	Net outflow (Outflow - Inflow)		Required net outflow		Total distance	
6	1	39				1						
7	1	41				2						
8	2	13				3						
9	2	17				4						
10	2	18				5						
11	2	27				6						
12	2	30				7						
13	2	34				8						
14	2	36				9						
15	4	12				10						
16	4	15				11						
17	4	25				12						
18	4	45				13						
19	5	15				14						
20	5	17				15						
21	5	34				16						
22	5	39				17						
23	5	42				18						
24	6	15				19						
25	6	26				20						
26	6	27				21						
27	6	29				22						
28	6	41				23						
29	6	45				24						
30	6	48				25						
31	6	49				26						
32	7	14				27						
33	7	16				28						
34	7	36				29						
35	10	3				30						
36	11	47				31						
37	12	4				32						
38	12	15				33						
39	12	45				34						
40	13	30				35						
41	14	7				36						
42	14	25				37						
43	14	37				38						
44	14	38				39						
45	15	2				40						
46	15	4				41						
47	15	5				42						
48	15	6				43						
49	15	12				44						
50	15	18				45						
51	15	34				46						
52	15	39				47						
53	15	40				48						
54	16	7				49						
…												
191	49	27										
192	49	29										
193	49	36										
194	49	41										
195	49	46										

Specify Solver:

Set Objective: __________

To: ○ Max ○ Min ○ Value of: __________

By Changing Variable Cells: ____

Subject to the Constraints:

☐ Make Unconstrained Variables Non-Negative

Select a Solving Method: _____________

Solver Results:

The optimal total distance = _____.

The New York Times

February 7, 2010

SLIPSTREAM

Better Loving Through Chemistry

By NATASHA SINGER

IF finding true love were an exact science, we wouldn't need matchmakers, singles bars or, of course, online dating services.

Like job seekers who take the Myers-Briggs personality test to help steer them to suitable professions, we'd simply take a relationship test, whose results would identify our most compatible types of mates and rule out the frogs. Problem solved.

Of course, Cosmopolitan magazine has been running pop psychology love quizzes — "Which Bachelor Is Right for You?," "Is He Naughty or Nice?" — for decades, prompting young women the world over to assess how sexually or socially compatible they might be with their objects of desire.

Now, a handful of dating Web sites are competing to impose some science, or at least some structure, on the quest for love by using different kinds of tests to winnow the selection process. In short, each of these sites is aiming to be the Netflix of love.

Instead of using a proprietary algorithm to recommend movies you might enjoy, based on your past choices, however, these dating sites offer you a list of romantic candidates whose selection is based on proprietary analyses of personality characteristics or biological markers.

Consider ScientificMatch.com, founded about two years ago, which aims to create romantic chemistry via genetic testing. The site, which matches people based on certain genetic markers for the immune system, takes its cue from studies showing that women are more attracted to the smell of men who have very different immune systems from their own. The site charges $1,995.95 for a lifetime membership — the lofty fee includes a cheek swabbing kit, DNA processing, a criminal and bankruptcy background check, as well as verification of age and marital status, the site says.

Then there's Chemistry.com, started in 2006 by the dating giant Match.com. Helen Fisher, the biological anthropologist who developed Chemistry.com's questionnaire, says the site is designed to predict compatibility based on traits of temperament like adventurousness, decisiveness or empathy. And it charges a premium for its services: about $50 for a one-month membership, compared with about $35 for Match.com.

But both ScientificMatch.com and Chemistry.com are refinements of an idea originally developed by eHarmony.com.

Founded in 2000 by a psychologist with experience in marriage counseling, eHarmony focuses on singles willing to invest time and to pay premium prices to find a long-term partner. People who register with the site fill out a long questionnaire that is intended to match people based on similarities in sociological variables like values, family background and social styles. Membership can cost up to $45.95 a month.

Online dating is a $976 million annual industry in the United States, according to estimates from Marketdata Enterprises, a research firm. So, to stand out among hundreds of mass-market, open-community sites that attract everyone from people trolling for quick hookups to those headed for holy matrimony, a few services offer more elaborate mate-finding methods.

They build brand identity when they “target people who are looking for relationships rather than just dating,” says John LaRosa, the research director at Marketdata Enterprises. That means matchmaking sites with fewer users can charge more per subscriber than larger sites that list online personals.

Match.com, with an estimated 1.2 million paid subscribers, had revenue of about $365 million in 2008, Mr. LaRosa estimates. EHarmony, meanwhile, with about 656,000 paid members, had estimated revenue of $216 million that year, he says. But do partner-prediction sites do better at matching people than less-structured dating sites where people seek, sort and select others on their own?

Success rates for online dating are hard to measure. But eHarmony says it clearly enhances the process by catering to people who are looking for relationships leading to marriage.

People tend to be adept at heeding that first spark of attraction but may be less dexterous at recognizing the commonalities that are the foundations of good marriages, says Gian Gonzaga, eHarmony’s senior director of research and development. The site suggests potential matches based on areas of compatibility —like values, beliefs and important experiences — that are predictors of relationship success, he says.

“In the long haul, you want to be able to manage conflicts, celebrate positives and get through the day-to-day relationship,” Dr. Gonzaga said. “Our system is there to take care of that so you can now focus on who you find really attractive, that you feel really passionate about.”

Chemistry.com, meanwhile, uses answers to a detailed questionnaire to suggest potential partners based on their brain chemistry, says Dr. Fisher, a research professor in the anthropology department at Rutgers University. Based on a review of scientific studies on neurotransmitters and chemicals like dopamine in the brain, she determined that humans tend to express one of four dominant temperaments.

Since the site’s introduction in 2006, more than eight million people have answered Dr. Fisher’s questionnaire, and she has used their answers to pinpoint traits that attract people to one another. She says people of decisive, straight-talking temperament, whom she calls “directors,” tend to be attracted to empathetic, intuitive types she calls “negotiators.” Spontaneous types (“explorers”) tend to be attracted to their own kind, while traditional pillars of society (“builders”) also tend to seek out partners that resemble themselves.

“If Helen Fisher can give you right off the bat individuals that your brain is more likely to be attracted to,” she says, “so much the better.”

At the end of the day, however, it may be that the success of such sites is attributable not so much to their proprietary methods as to their choosy, self-selected members who don’t want to wink at and woo the first person whose profile they read online. The sites attract cohorts of people interested in slowing down the online dating and mating process, in finding out more information about potential partners — or in ruling out unlikely suitors — before they graduate to the meet-and-greet stage.

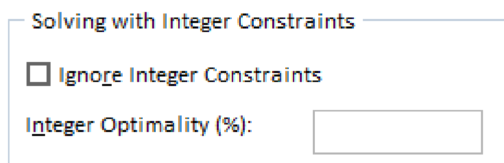
THE more advanced the partner prediction sites, the more they may actually serve a more old-fashioned role. The sites provide background details on a person’s family, education, aspirations, character, genetic traits and general health of the type that was once public information in farming or immigrant communities or even in hunter-gatherer societies, Dr. Fisher says.

Indeed, at least from the point of view of evolutionary science, you’d be better off spending $50 — and more likely to find a mate — by using a premium dating site than by dropping $50 on drinks in the uncertain waters of singles bars.

Integer Programming

- Integer programming models are harder to solve than linear programming models.
  - It takes longer for Solver to find a solution for integer programming problems.
  - Sometimes Solver can only find a ____________________ solution.

- In Solver → Options,



Integer Programming

- Integer variables
  - Examples: number of ads, etc.
- Binary variables (0-1 variables)
  - Examples: whether a social link is on the shortest path or not, whether Netflix should open a distribution center in South Bend or not, etc.

Example: Dream Team Formation

Coach Brey is faced with the decision of selecting 7 star players for the Dream Team. He has narrowed his choice down to 10 players. For each player, Coach Brey has collected some statistics (1 being best, and 5 being worst) for the players. In addition, players can only play certain positions of the lineup. The positions that each player is allowed to play and the player's assists, scoring, rebound and defense skills are listed in the table below.

Player	Position	Assists	Scoring	Rebounding	Defense
1	G	3	4	2	1
2	C	2	1	3	4
3	G-F	4	2	2	4
4	F-C	1	3	3	1
5	G-F	5	2	1	2
6	F-C	4	1	2	3
7	G-F	3	5	3	1
8	G-C	2	3	4	1
9	F	2	2	2	5
10	G-F	3	3	1	2

In order to have a well-rounded team, the coach knows he must fulfill the following requirements:

1. At least two members must be able to play guard (G), at least four members must be able to play forward (F), and at least two players must be able to play center (C) (some players have to be versatile).
2. The average assists, rebounding, and defense level of the 7 star players must be better than 4. (Keep in mind, 1 is best and 5 is worst)
3. If player 4 is on the team, then player 5 cannot be on the team (Players have compatibility issues!).
4. Players 3 and 9 must be selected together because they feel they are most effective when they play together (so either both or neither are selected).
5. Either player 3 or player 4 (or both) must be included because they are the ones that bring in the fans.

Given these constraints, Coach Brey wants to maximize the total scoring ability of the Dream team. Who should be in the dream team?

Excel Setup:

	A	B	C	D	E	F	G	H	I	J
1	**Dream Team Formation**									
2										
3	Player	G	F	C	Assists	Scoring	Rebounding	Defense		Pick?
4	1	1	0	0	3	4	2	1		
5	2	0	0	1	2	1	3	4		
6	3	1	1	0	4	2	2	4		
7	4	0	1	1	1	3	3	1		
8	5	1	1	0	5	2	1	2		
9	6	0	1	1	4	1	2	3		
10	7	1	1	0	3	5	3	1		
11	8	1	0	1	2	3	4	1		
12	9	0	1	0	2	2	2	5		
13	10	1	1	0	3	3	1	2		
14										
15										
16		**Total # of players for each position in the dream team**			**Average skills of the dream team**					**Total # of players**
17										
18	**Objective:**									
19	Total scoring ability:									

Specify Solver:

Set Objective: __________

To: ○ Max ○ Min ○ Value of: __________

By Changing Variable Cells: ____

Subject to the Constraints:

☐ Make Unconstrained Variables Non-Negative

Select a Solving Method: ____________

Solution:

	A	B	C	D	E	F	G	H	I	J
1	**Dream Team Formation**									
2										
3	Player	G	F	C	Assists	Scoring	Rebounding	Defense		Pick?
4	1	1	0	0	3	4	2	1		
5	2	0	0	1	2	1	3	4		
6	3	1	1	0	4	2	2	4		
7	4	0	1	1	1	3	3	1		
8	5	1	1	0	5	2	1	2		
9	6	0	1	1	4	1	2	3		
10	7	1	1	0	3	5	3	1		
11	8	1	0	1	2	3	4	1		
12	9	0	1	0	2	2	2	5		
13	10	1	1	0	3	3	1	2		
14										
15										
16		**Total # of players for each position in the dream team**			**Average skills of the dream team**					**Total # of players**
17										
18	**Objective:**									
19	Total scoring ability:									
20										
21	Calculations for Constraints:									
22										
23										
24										
25										

Crew Scheduling

- Examples of crew scheduling
  - Scheduling worker times for supermarkets, hospitals, department stores, telephone operators, airlines, hotels, restaurants, factories, maintenance staffs, security services, toll collectors, etc.
- The planning horizon is the time into the future during which staffing decisions must be made.
  - It is broken down into time periods: hours, days, shifts, weeks, etc.
- A demand pattern is a list of the number of workers (possibly broken down by job classification) needed during each period of the planning horizon.

A General Crew Scheduling Problem

- We have a demand pattern over a planning horizon and a list of current workers.
- A list of candidate schedules is generated for each worker.
- Each worker can rate the desirability of each of his/her candidate schedules.
- We want to pick one schedule for each worker so that demand is covered and worker satisfaction is maximized.

GRAND HYATT NEW YORK

FRONT OFFICE SCHEDULE

MONTH: MARCH	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
REGISTRATION:	3/30	3/31	4/1	4/2	4/3	4/4	4/5
Molly	7 REG	7 REG	R	7 CASH	7 CASH	R	9 CASH
Lynn		M O	D E L	U N			
Martha	B4	B4	B4	B4			B4
Mary	4	4	4			4	4
Susan		3	3		4	3	2
Lisa	8			3	3	2	9
LJ		7	7	7	7	7	
Joanne	3	2	2	2	2		
Grace			4	4	B4	B4	3
David	5			5	5	3	5
Una			7	7	7	7	7
Michelle	7	8	8	10	10		
Denise	12	3	R		12	10	10
Mink	12	12	12	12	12		
Michael	R	R	8 CASH	8 REG	8 CASH	8 CASH	8 CASH
Trainee Edith	9 ORIENT	9	9	9	9		
CASHIER:							
Mita	5	5	5	5	R	5	R
Joel	10	10	10	10	10		
Craig	7	7			R	R	R
Helen	3		3	3	4		4
Maggie	7	7			7	7	7
Donna			7	7	9	7	7
Annette	R	8	7	8	R	10	10
Lauren			VACATION				
Night Audit:							
Heather	11pm	R	R	12	11	12	12
Gary			VACATION				
Toan	R	11	11	11	R	11	11
Manita (Training)	12pm	12	12	12	12		
Supervisors:							
Shawn Credit	4	4			4	4	4
Stephanie		9	9	9	9		7
Rob	3	3	R	12	3	12	R
Tom			8pm	4	9pm FLASH	4	3
Bill	3	3	3	3	R	R	3
Larry	9PM FLASH	8PM FLASH			3	3	12
Elizabeth	7	7	12	7	7	R	R
Charys		R	7	7	7	7	R
Mary	7	7	7	R	R	7	7
Darryl > Assistant	12	12	3		7	8	
Joel	7	7	7	7	R	R	7
Demand ARRIVALS:	535	550	600	505	520	530	425
DEPARTURES:	280	530	530	560	670	360	605
OCCUPANCY:	965	975	1035	970	810	970	780

SCHEDULE VARIABLES

Business analysis:

Monday-Thursday: We are basically a Corporate Traveler's hotel during these days. Our peak check-in hours are: 5:00-9:00p.m. Our peak check-out hours are: 6:00-9:00a.m.

Friday&Saturday:We turn into a weekend traveler's hotel. Our peak check-in hours are: 11:00-4:00p.m. Our peak check-out hours are: 11:00a.m.-2:00p.m.

Sunday: Peak check-in hours are: 6:00-9:00p.m. peak check-out hours same as Fri&Sat 11:00a.m.-2:00p.m.

Work Shifts:

On the Registration side (check-in): The shifts start at 7:00a.m. and can be spread out throughout the day.
On the Cashiering side (check-out): The shifts start at 6:00a.m., it is helpful to have a swing shift to help cover lunch breaks. The cashiers have to leave their shift 45 minutes prior in order to "bank out" their days work.
On the Night Audit side: The shifts are 11:00 p.m.-7:00a.m and 12:00p.m.-8:00a.m. You must always have at least two on each shift.
Supervisors & Assistants: Their are 8 supervisors and two assistants. A comfortable day would be to have 3 a.m. opening supervisors starting at 7:00a.m. and 2-3 p.m. supervisors starting at 3:00-4:00p.m. and one swing shift at 12:00noon. The assistants should be one in the morning 7:00a.m. and one split shift 12:00. The manager usually takes off Sat.&Sun. and one of the assistants should be scheduled on those days.

Staffing Guide:

The staffing guide can be used as a guideline as to how many clerks you need scheduled for the number of arrivals and departures for that day. (See the very bottom of the schedule.)

Employee Requests:

The employees have the opportunity to request specific days off so they change each week. There are a few employees who have classes and their schedules are set each week. They are as follows:

LJ: Has class M-F at 8:00p.m.
Joanne: Has to work midday shifts
Lisa: Sat.&Sun. schedule after 8:00a.m. due to train commute.
Susan: Tues. class from 11-12noon
Thur. class 5-7p.m.
Sat.class 11-1p.m.
Molly: Wed.&Sat. classes
Martha: Is what we call the BUCKET person (B4 is noted on the schedule) Her alternate person is Grace.

Example: Crew Scheduling

Set up the Crew Scheduling model in Excel:

	A	B	C	D	E
1	**Crew Scheduling**				
2					
3	Worker Satisfaction				
4					
5					
6		Weights	Sch Limit	Sch Limit Targets	Variables
7	Bob	1			
8		4			
9		5			
10	Bill	3			
11		3			
12		4			
13	Joe	6			
14		3			
15		1			
16	Sylvia	1			
17		5			
18		4			
19	Joann	2			
20		2			
21		6			
22	Mary	3			
23		6			
24		1			
25					
26				Number working	
27					
28				Requirements	

Proposed Two-Week Schedules

Day shift

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
7	1	1	1	1	1			1	1	1	1	1		
8	1	1	1	1	1									
9														
10			1	1	1	1	1							
11										1	1	1	1	1
12														
13														
14														
15														
16														
17	1	1	1	1			1							
18								1	1	1	1			1
19		1	1	1	1	1			1	1	1	1	1	
20														
21														
22	1	1	1			1	1							
23														
24														
28	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Evening shift

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
7														
8								1	1	1	1	1		
9	1	1	1	1	1									
10										1	1	1	1	1
11			1	1	1	1	1							
12														
13														
14								1	1			1	1	1
15	1	1			1	1	1	1	1			1	1	1
16	1	1	1	1			1							
17								1	1	1	1			1
18	1	1	1	1			1							
19														
20		1	1	1	1	1			1	1	1	1	1	
21														
22								1	1	1			1	1
23														
24	1	1	1			1	1	1	1	1			1	1
28	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Night shift

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
7														
8														
9								1	1	1	1	1		
10														
11														
12			1	1	1	1	1			1	1	1	1	1
13	1	1			1	1	1	1	1			1	1	1
14	1	1			1	1	1							
15														
16								1	1	1	1			1
17														
18														
19														
20														
21		1	1	1	1	1			1	1	1	1	1	
22														
23	1	1	1			1	1	1	1	1			1	1
24														
28	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Example: Crew Scheduling

Solver Solution:

	A	B	C	D	E
1	**Crew Scheduling**				
2					
3	Worker Satisfaction	26			
4					
5					
6		Weights	Sch Limit	Sch Limit Targets	Variables
7	Bob	1	1	1	0
8		4			1
9		5			0
10	Bill	3	1	1	0
11		3			1
12		4			0
13	Joe	6	1	1	1
14		3			0
15		1			0
16	Sylvia	1	1	1	0
17		5			0
18		4			1
19	Joann	2	1	1	0
20		2			0
21		6			1
22	Mary	3	1	1	1
23		6			0
24		1			0
25					
26				Number working	
27					
28				Requirements	

	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	AA	AB	AC	AD	AE	AF	AG	AH	AI	AJ	AK	AL	AM	AN	AO	AP	AQ	AR	AS	AT	AU	AV
3	**Proposed Two-Week Schedules**																																									
4	**Day shift**														**Evening shift**														**Night shift**													
5	1	2	3	4	5	6	7	8	9	10	11	12	13	14	1	2	3	4	5	6	7	8	9	10	11	12	13	14	1	2	3	4	5	6	7	8	9	10	11	12	13	14
6																																										
7	1	1	1	1	1			1	1	1	1	1																														
8	1	1	1	1	1																	1	1	1	1	1																
9															1	1	1	1	1																	1	1	1	1	1		
10			1	1	1	1	1																	1	1	1	1	1														
11										1	1	1	1	1			1	1	1	1	1																					
12																															1	1	1	1	1			1	1	1	1	1
13																													1	1			1	1	1	1	1			1	1	1
14																						1	1			1	1	1	1	1			1	1	1							
15															1	1			1	1	1	1	1			1	1	1														
16															1	1	1	1			1															1	1	1	1			1
17	1	1	1	1			1															1	1	1	1			1														
18								1	1	1	1			1	1	1	1	1			1																					
19		1	1	1	1	1			1	1	1	1	1																													
20																1	1	1	1	1			1	1	1	1	1															
21																														1	1	1	1	1			1	1	1	1	1	
22	1	1	1			1	1															1	1	1			1	1														
23																													1	1	1			1	1	1	1	1			1	1
24															1	1	1			1	1	1	1	1			1	1														
25																																										
26	2	2	2	1	1	1	1	1	1	2	2	1	1	2	1	1	2	2	1	1	2	2	2	2	1	1	1	1	1	2	1	1	2	2	1	1	2	1	1	2	2	1
27	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=	>=
28	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

The New York Times

The Art and Science of Scheduling Meet in the N.F.L. Office

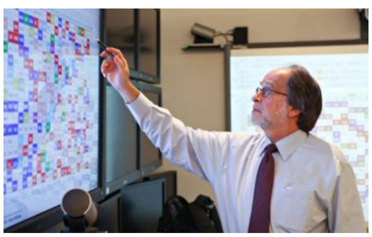
By JUDY BATTISTA

April 19, 2012

The e-mail was finally sent to Roger Goodell at 12:33 a.m. Monday — "White smoke from the scheduling room." That one line put an end to the N.F.L.'s yearly eye-blurring, mind-bending exercise in juggling the absurd and the inconvenient, in balancing prime-time television and 10 a.m. body clocks for West Coast teams, in sifting through 14,000 potential schedules to find the one that pleases the most and infuriates the least.

But even in the hours before the 2012 regular-season schedule was released to the public Tuesday night — setting off hours of analysis of matchups whose existence, though not their timing, had been known for months — the calls and texts kept coming into the small room at the N.F.L's Park Avenue headquarters outfitted with five computers, a gigantic monitor and a critical shredder.

There were complaints and questions and the occasional compliment from teams and television networks that had spent the last two and a half months lobbying the scheduling department for their preferred combination of games, and who are likely to continue to vent and question or marvel at the schedule's sometimes accidental foresight, until it is time to start planning for 2013.



"This is the annual ritual of finding out how stupid I am," said Howard Katz, the N.F.L.'s scheduling czar. "We work for months and months in this room and 'What were they thinking?' It comes with the territory."

After recalling what he thought was a coup last year — putting a game between the New Orleans Saints and the Indianapolis Colts on the Sunday night opposite the World Series, only to watch the Saints obliterate a Peyton Manning-less Colts team, 62-7 — Katz summed up the snap judgments of the schedule that are as quick to change as a channel.

"We're geniuses one day and absolute morons the next," he said.

For the networks that pay billions of dollars to carry N.F.L. games, they have been mostly geniuses. N.F.L. games were watched by an average of 17.5 million viewers last season, the second most since 1989, and off slightly from 2010. N.F.L. games accounted for 23 of the 25 most-watched television shows among all programming, and the 16 most-watched shows on cable last fall.

Designing a schedule that generates those ratings, while also guaranteeing competitive fairness, is more complicated than ever, even though a computer program in use for eight years now does some of the work that was once done entirely by hand — spitting out 400,000 complete or partial schedules from a possible 824 trillion game combinations.

Katz's department must consider a confounding array of factors, from the N.F.L.'s expanded Thursday night package, which gives each team a game in a short week, to potential baseball playoff situations that could affect the availability of stadiums and parking lots in October. The summer is spent rooting against certain baseball teams that share facilities with football teams. When baseball began awarding home-field advantage in the World Series to the winning league in the All-Star Game, it further complicated the task.

"We walk out of here the night of the All-Star Game and say, 'Who are we rooting for?' " said Onnie Bose, a member of the scheduling staff.

The process gets serious in January, when teams submit lists of requests detailing stadium availability and preferences for scheduling order. This year, teams submitted more than 70 blocked-out dates for stadiums — the Jets and the Giants are both on the road in Week 3, for instance, because Bruce Springsteen will be performing at MetLife Stadium — and 100 requests, from the sublime to the ridiculous.

Florida teams often ask not to play 1 p.m. games in September and October, believing it is more difficult to sell tickets in broiling heat; sometimes the same organization will submit different requests because coaches believe the heat provides a competitive advantage. Southern teams do not want to go north late in the season. Teams that struggle to sell tickets worry especially about their late-season schedule.

There are requests not to play at home on certain holidays — the Jets and the Giants typically ask not to play home games during the Jewish High Holy Days. When the N.F.L. put the Jets at home on Rosh Hashana and the start of Yom Kippur in 2009, Katz heard about it from the team. And others.

"I heard from every rabbi — 'How could you screw that up?' " Katz said. (On Thursday, the N.F.L. moved the start of the Raiders-Dolphins game in Miami on Sept. 16 — Rosh Hashana — up from 4:15 p.m. to 1 p.m. to give Jewish fans more time to be home before the holiday starts at sundown.)

The Jets asked to host the Thanksgiving night game this year. Jonathan Payne, another member of the scheduling group, opened a folder with more requests.

"No games against teams coming off their bye," he read.

During Super Bowl week, Katz meets with representatives from each of the networks that carry N.F.L. games, receiving wish lists from NBC, ESPN and the NFL Network for games they want in prime time, and lists — often nearly identical — from Fox and CBS of games they do not want to lose from their Sunday afternoon slots.

Among observers, NBC is viewed as getting the best treatment because of the cachet of the popularity of football on broadcast television. ESPN hopes for plenty of division games because there is almost always something on the line. Last year, NBC and Fox wrestled over the regular-season finale between the Cowboys and the Giants, a guaranteed ratings bonanza. The N.F.L. moved the matchup — which determined which team went to the playoffs — to NBC for the second time in the season, upsetting Fox so much that Katz said the network's lead analyst, Troy Aikman, stopped speaking to him.

Katz's department starts with thousands of seed schedules, empty slates in which a handful of critical games with attractive story lines are placed in select spots. Then the computers generate possibilities around those games. The N.F.L. also feeds the computer with penalties for situations it prefers to avoid — three-game trips, for example, or teams starting with two road games.

The Pittsburgh-Denver game in the first week on Sunday night was an early favorite for that spot because it was a rematch of a playoff game and would have featured a ratings juggernaut with Tim Tebow. Then Denver signed Peyton Manning and Tebow was traded to the Jets. The N.F.L. reconsidered, then left the game in the slot. Manning's move to Denver did not change the schedule as much as might have been thought because the Broncos were likely to get considerable prime-time consideration with Tebow. Nor did the Saints' recent strife because Katz and his crew think New Orleans will still be a good team without Coach Sean Payton.

This year, the computers generated 14,000 playable schedules, which were reduced to 150 with an eyeball test. Then the scheduling department reviewed those 150 by hand, scoring them for each team and each network.

"It's part art and part science," said Michael North, who works closely with Katz. "The science is the needle in the haystack may be so far over here that the computer cannot search through the entire space. What if that seed schedule had one game in the wrong spot and that one game prevented us from looking at that part of the haystack?"

A few weeks ago, Katz's department had a schedule it loved, until it realized one team had a three-game trip heading into a Thursday night game. The schedule was tossed.

Finally, late Sunday, after the computers had run one last time, the department settled on the schedule it reviewed with Goodell for two hours Monday and announced Tuesday.

That will undoubtedly not be the last they hear about it.

At the league meeting last month, Katz was approached by Baltimore Coach John Harbaugh and told he had to meet his brother. Jim Harbaugh, John's brother and the coach of the San Francisco 49ers, was upset that his team had been sent across the country for last year's Thanksgiving night game against his brother's team.

"I talked to him, then I talked to him the next day and then I talked to him the third day," Katz said of Jim Harbaugh. "He said, 'Now that I've met you, I don't hate you quite as much.' His brother said to me, 'That's as good as you're going to do.' "

Nonlinear Programming

- Examples of nonlinear relationships
  - Consumer demand as a function of product price

Example: Rating College Football Teams

- Sports fans always wonder which team is best in a given sport. You might be surprised to learn that Solver can be used to rate sports teams.
- In this example, we use a nonlinear programming model to rate college football teams.
- We obtain the results of college football games during the 2012 regular season and entered the data into a spreadsheet.
- Our goal is to determine a set of ratings for the 124 NCAA Division I FBS teams that most accurately predicts the actual outcomes of the games played.

Example: Rating College Football Teams

Set up the Rating model in Excel:

	A	B	C	D	E	F	G	H	I	J	K	L
1	**Rating College Football Teams (2012)**				**Objective to minimize**							
2					**Sum squared errors**							
3	Home game advantage											
4					**Results of games**						**Model predictions and errors**	
5	Constraint on average rating (any nominal value could be used)				Week	Home Team	Visiting Team	Home Team Score	Visiting Team Score	Point spread	Predicted spread	Squared error
6	Actual average				1	Akron	Central Florida	14	56			
7		=			1	Ball State	Eastern Michigan	37	26			
8	Nominal average	85			1	Vanderbilt	South Carolina	13	17			
9					1	Rice	UCLA	24	49			
10	**Ratings of teams**				1	Connecticut	Massachusetts	37	0			
11	Team Index	Team Name	Rating		1	BYU	Washington State	30	6			
12	1	Air Force			1	UNLV	Minnesota	27	30			
13	2	Akron			1	North Carolina State	Tennessee	21	35			
14	3	Alabama			1	Michigan State	Boise State	17	13			
15	4	Arizona			1	Stanford	San Jose State	20	17			
16	5	Arizona State			1	Navy	Notre Dame	10	50			
17	6	Arkansas			1	Illinois	Western Michigan	24	7			
18	7	Arkansas State			1	Iowa State	Tulsa	38	23			
19	8	Army			1	UAB	Troy	29	39			
20	9	Auburn			1	Ohio State	Miami (Ohio)	56	10			
21	10	Ball State			1	Penn State	Ohio	14	24			
22	11	Baylor			1	Syracuse	Northwestern	41	42			
23	12	Boise State			1	West Virginia	Marshall	69	34			
. . .												
132	121	Western Kentucky			3	Indiana	Ball State	39	41			
133	122	Western Michigan			3	Michigan State	Notre Dame	3	20			
134	123	Wisconsin			3	San Jose State	Colorado State	40	20			
135	124	Wyoming			3	LSU	Idaho	63	14			
136					3	Mississippi	Texas	31	66			
. . .												
664					13	Southern Cal	Notre Dame	13	22			
665					13	San Jose State	Louisiana Tech	52	23			
666					13	Hawaii	UNLV	48	10			
667					14	Rutgers	Louisville	17	20			
668					14	Kent State	Northern Illinois	37	44			
669					14	Stanford	UCLA	27	24			
670					14	TCU	Oklahoma	17	24			
671					14	Baylor	Oklahoma State	41	34			
672					14	Tulsa	Central Florida	33	27			
673					14	West Virginia	Kansas	59	10			
674					14	Arkansas State	Middle Tennessee	45	0			
675					14	Florida Atlantic	Louisiana-Lafayette	21	35			
676					14	Connecticut	Cincinnati	17	34			
677					14	Nevada	Boise State	21	27			
678					14	Georgia	Alabama	28	32			
679					14	Texas State	New Mexico State	66	28			
680					14	South Florida	Pittsburgh	3	27			
681					14	Georgia Tech	Florida State	5	21			
682					14	Kansas State	Texas	42	24			
683					14	Wisconsin	Nebraska	70	31			
684					14	Hawaii	South Alabama	23	7			
685					15	Army	Navy	13	17			

Specify Solver:

Set Objective: __________

To: ○ Max ○ Min ○ Value of: __________

By Changing Variable Cells: ____

Subject to the Constraints:

☐ Make Unconstrained Variables Non-Negative

Select a Solving Method: _____________

Solver Results:

	A	B	C	D	E	F	G	H	I	J	K	L
1	**Rating College Football Teams (2012)**				**Objective to minimize**							
2					**Sum squared errors**	105147.94						
3	Home game advantage	3.65										
4					**Results of games**						**Model predictions and errors**	
5	Constraint on average rating (any nominal value could be used)				Week	Home Team	Visiting Team	Home Team Score	Visiting Team Score	Point spread	Predicted spread	Squared error
6	Actual average	85.00			1	Akron	Central Florida	14	56	-42	-26.15	251.21
7		=			1	Ball State	Eastern Michigan	37	26	11	18.91	62.49
8	Nominal average	85			1	Vanderbilt	South Carolina	13	17	-4	-5.57	2.47
9					1	Rice	UCLA	24	49	-25	-18.39	43.67
10	**Ratings of teams**				1	Connecticut	Massachusetts	37	0	37	30.60	40.93
11	Team Index	Team Name	Rating		1	BYU	Washington State	30	6	24	24.34	0.11
12	1	Air Force	77.41		1	UNLV	Minnesota	27	30	-3	-4.74	3.03
13	2	Akron	59.52		1	North Carolina State	Tennessee	21	35	-14	-2.04	143.14
14	3	Alabama	118.45		1	Michigan State	Boise State	17	13	4	0.17	14.63
15	4	Arizona	94.34		1	Stanford	San Jose State	20	17	3	12.52	90.56
16	5	Arizona State	98.01		1	Navy	Notre Dame	10	50	-40	-22.68	299.88
17	6	Arkansas	83.70		1	Illinois	Western Michigan	24	7	17	-0.44	304.19
18	7	Arkansas State	91.23		1	Iowa State	Tulsa	38	23	15	12.65	5.54
19	8	Army	68.35		1	UAB	Troy	29	39	-10	-11.98	3.91
20	9	Auburn	80.51		1	Ohio State	Miami (Ohio)	56	10	46	36.98	81.31
21	10	Ball State	80.24		1	Penn State	Ohio	14	24	-10	22.56	1059.85
22	11	Baylor	100.14		1	Syracuse	Northwestern	41	42	-1	1.24	5.04
23	12	Boise State	94.26		1	West Virginia	Marshall	69	34	35	25.32	93.75
…												
132	121	Western Kentucky	83.14		3	Indiana	Ball State	39	41	-2	1.01	9.08
133	122	Western Michigan	71.26		3	Michigan State	Notre Dame	3	20	-17	-11.94	25.64
134	123	Wisconsin	98.66		3	San Jose State	Colorado State	40	20	20	25.50	30.21
135	124	Wyoming	75.95		3	LSU	Idaho	63	14	49	52.45	11.89
136					3	Mississippi	Texas	31	66	-35	-4.32	941.25
…												
664					13	Southern Cal	Notre Dame	13	22	-9	-1.16	61.45
665					13	San Jose State	Louisiana Tech	52	23	29	10.33	348.56
666					13	Hawaii	UNLV	48	10	38	-1.90	1592.02
667					14	Rutgers	Louisville	17	20	-3	5.07	65.10
668					14	Kent State	Northern Illinois	37	44	-7	-5.63	1.87
669					14	Stanford	UCLA	27	24	3	9.08	36.92
670					14	TCU	Oklahoma	17	24	-7	-8.94	3.75
671					14	Baylor	Oklahoma State	41	34	7	-1.92	79.60
672					14	Tulsa	Central Florida	33	27	6	1.80	17.66
673					14	West Virginia	Kansas	59	10	49	19.83	850.74
674					14	Arkansas State	Middle Tennessee	45	0	45	13.91	966.78
675					14	Florida Atlantic	Louisiana-Lafayette	21	35	-14	-8.74	27.64
676					14	Connecticut	Cincinnati	17	34	-17	-13.12	15.07
677					14	Nevada	Boise State	21	27	-6	-6.25	0.06
678					14	Georgia	Alabama	28	32	-4	-7.90	15.22
679					14	Texas State	New Mexico State	66	28	38	22.69	234.36
680					14	South Florida	Pittsburgh	3	27	-24	-10.56	180.75
681					14	Georgia Tech	Florida State	5	21	-16	-13.63	5.61
682					14	Kansas State	Texas	42	24	18	13.33	21.77
683					14	Wisconsin	Nebraska	70	31	39	8.24	946.03
684					14	Hawaii	South Alabama	23	7	16	-0.74	280.08
685					15	Army	Navy	13	17	-4	-8.04	16.35

The procedure used in this example is practically identical to the procedure used in the Jeff Sagarin NCAA football ratings, which is one of the six computer rankings used in calculating the BCS Average.

Two main reasons that our rating results are different from the real Jeff Sagarin NCAA football rating results submitted to BCS.

- In the real Jeff Sagarin NCAA football ratings, both Division I FBS and Division I FCS teams are considered, i.e., 246 teams instead of 124 teams are considered.
- In the real Jeff Sagarin NCAA football ratings, only winning and losing matters, i.e., the score margin is of no consequence, which makes it very "politically correct".

Find out more about the Jeff Sagarin NCAA football ratings at
http://usatoday30.usatoday.com/sports/sagarin/fbt12.htm

THE WALL STREET JOURNAL.
WSJ.com

SCIENCE JOURNAL
April 23, 2004

Did You Hear the One About the Salesman Who Traveled Better?

By SHARON BEGLEY | Staff Reporter of THE WALL STREET JOURNAL

Traveling salesmen star in more jokes than almost any other occupation, but William Cook doesn't let that distract him.

A mathematician at Georgia Institute of Technology, Atlanta, Prof. Cook is one of hundreds of researchers who, since the 1930s, have wracked their brains over the puzzle known as the traveling-salesman problem. It asks: What's the shortest itinerary a salesman can follow to visit all the stops on his route?

If our Willy Loman has to make only three or four stops, the optimal route is easy to figure out. But once he adds a few dozen, the number of possible sequences grows exponentially, and the computer time it would take to calculate every possibility grows into the decades. As a result, after three mathematicians solved the problem for 49 cities in 1954, it took until 1971 to solve it for only 15 more. But Prof. Cook and three colleagues broke the problem wide open in the 1990s, solving it for 13,509 cities in 1998 and for 24,978 a few weeks ago. That feat took 67 computer years. (You can see the optimal paths at www.math.princeton.edu/tsp/vlsi/index.html.)

While not even the busiest salesman has a route that big, the problem has become a boldface celebrity in the business world because all manner of practical problems involve the basic question, what is the best way to do something? Applications range from scheduling cable-TV service calls and routing parcel-delivery trucks to drilling holes in a circuit board, where you want to minimize how far the drill, like the salesman, must travel.

Faster computers are still not fast enough for this task, because such problems have zillions of possible combinations, notes Michael Trick of Carnegie Mellon University, Pittsburgh. UPS, for one, has upward of 1,500 pick-up/delivery facilities and sorting centers. It would take millennia of computer hours to solve its routing problems using the traditional problem-solving methods. So, scientists in "operations research" (a hybrid of math, engineering and computer science) now are exploiting what Prof. Trick calls "profound insights into the mathematics of the problem." In other words, they're figuring out clever shortcuts the computers can take.

These insights take the form of algorithms, a sort of mathematical recipe. "We're developing algorithms that are 10,000 times faster than the ones we used 15 years ago," says Irv Lustig, an operations researcher at ILOG Inc., Mountain View, Calif. "Now we can say, given the data, here is the probably-best answer."

An algorithm he developed for ILOG, which sells algorithm-packed custom software, tackled the National Football League's 2004 schedule. He had to juggle 256 games among 32 teams, subject to multiple constraints. There had to be a nationally appealing game every Monday night and at least one must-see match-up every Sunday, for example, and he couldn't send a team on the road for weeks at a time.

Dr. Lustig's algorithm created thousands of schedules that fit these constraints in a fraction of the time it took by trial-and-error computing. Even better, it can tweak a schedule in less than a day if, say, the NFL decides that a

Giants-Redskins game simply won't do for Week 8 (it's Week 2). In the past, making that change would produce a domino effect taking days to fix.

Many of the new algorithms emerged from advances in a relatively young field of math called linear programming. Despite its name, linear programming is not a kind of software-writing. Instead, it's a way to solve optimization problems. Among the most powerful algorithms in linear programming is one that could use some help from a branding consultant, but for now is called the "interior-point method."

Imagine that every possible solution to a problem is represented as a point on the surface of a million-faceted diamond. The best solution is the one at the top. The challenge is to reach it. Traditionally, you'd do that by climbing (mathematically) from point to higher point along the outside of the diamond. The interior-point method lets you zoom up the inside. Depending on the number of facets on the diamond, that may let you find the solution more quickly.

Thanks to abstruse breakthroughs like this, operations research (OR) has scored in more than the NFL. To eliminate backtracking and overlapping routes, Waste Management Inc. solved what you might call a traveling garbage-truck problem. Using an optimization algorithm to reroute its fleet, WMI eliminated 761 trucks, saved $91 million in annual operating costs and still hauled the trash on time.

So-called fractional-fleet services needed a similar mathematical rescue. These companies promise customers who own, say, one-quarter of a business jet that they can depart from anywhere within four hours. The easiest way to do that is to have a plane at every airport their customers use. But that is a good way to bleed cash. With operations research, Bombardier Flexjet was able to cut crew levels by 20%, while getting 10% more daily flights out of each of its aircraft.

Bombardier and WMI are among the finalists in a competition run by Informs, the professional group for operations research. The winner will be announced next week.

statesman.com

See the USA, in just over four days

Ben Wear, Getting There

Updated: 3:14 p.m. Monday, May 24, 2010
Published: 8:09 p.m. Sunday, May 23, 2010

The point of hobbies is there really is no point.

Case in point: the road trip that Central Texans Curtis and Ray Morriss began Friday and hope to complete Tuesday evening.

If things go as planned — and Curtis said late Sunday afternoon that so far they have — the Morriss brothers will have driven a car through every one of these Lower 48 United States in 100 hours, setting what they hope will be a record. They will have put about 6,850 miles on Curtis' Acura TSX (about 245 gallons, at what they estimate will be 28 miles per gallon, something like $750 for gasoline), stopping only for fueling and git-er-done-quick bathroom breaks, and grazing on a cache of food in the back seat.

They'll have passed through all of Woody Guthrie's America, from the Mississippi cotton fields to the George Washington Bridge in Manhattan, alongside Chicago's big highway shoulders, under Montana's sizable sky, past a great salt lake and finally a few feet into Arizona.

All to set a record. An unofficial record. Maybe. And perhaps for the second time in a year.

And to raise some money for a Leander school district volunteer program, though Curtis said the pledges have been minimal so far.

This trip is to transportation what scarfing a two-pound bag of M&M's is to eating. Empty travel calories made up mostly of interstate highways.

So, Curtis' wife, Kathy, back in Leander probably considers this behavior crazy, right?

"I don't know that she's actually used that word," he said. "There's been some other words like 'odd,' or 'strange,' or 'I don't get it.' "

The Morriss siblings are part of a fraternity of indeterminate size fascinated by the challenge of devising the most efficient way of driving through or barely grazing every state aside from Alaska and Hawaii (Washington, D.C., also gets skipped). There are even 10 rules for this, er, sport, according to the 48in96.com website, a production of one such group of explorers, Jay Lowe and Ted Jacobs. Lowe and Jacobs live in the Dallas-Fort Worth area.

Anyway, the website includes the rules first set out by the Guinness World Records people, plus what Lowe and Jacobs regard as the seminal rule: If you get a traffic ticket, the drive becomes invalid. The rules also stipulate that the start time and place be authenticated, and that there be two drivers and a nondriving navigator. Curtis says they have a GPS device that will digitally record the path of their trip.

Curtis, 47, a civil engineer with Baker-Aicklen & Associates Inc. in Round Rock, and Ray, 45, currently in between careers, will be ignoring that last rule. Which is OK, because Guinness is now ignoring these trips. Curtis says the Universe's Authority on mostness, fastness and bigness some years ago decided it was not so good to honor greatness in an activity that might involve inappropriate highway speeds. So, 48-state driving has devolved into a sort of Wild West affair.

Lowe and Jacobs, who in 1994 set the last official Guinness record of 118 hours and 15 minutes, on their website claim the current record of 104 hours and 57 minutes. They plan to go back out on the roads in June, the site says, and break the magic four-day barrier. Thus, 48-in-96.

Au contraire, Curtis would say, if engineers from Leander ever unholstered random French. Curtis says he and his brother did it in 101 hours and 29 minutes a year ago, their first attempt. The goal this time is 100 hours.

None of this occurs by happenstance. The route is carefully crafted to make the trip as short as possible (Lowe and Jacobs will no longer reveal their super-duper-secret map; the Morriss map is open to all), with 10 of what Curtis calls "U-turn states," places where they'll simply drive a few feet across a border to check that state off the list and then go back the other way.

They knocked the first three states off in the first minute. After leaving Austin on Friday morning, the Morrisses late that afternoon arrived at their starting point, the Downstream Casino Resort right on the Oklahoma-Missouri border. The parking lot is in Oklahoma, Morriss said, the driveway in Missouri and Kansas just three-tenths of a mile down the road. Boom, boom, boom, 45 to go.

Then it was across Arkansas and Dixie, up through the Mid-Atlantic and into the big Northeast cities on the weekend and, when possible, at night to ensure the least possible traffic. Trading off six-hour driving shifts while the other brother dozed, they were in Gary, Ind., late Sunday afternoon. By the time Statesman subscribers read this, the brothers should be barreling across South Dakota.

Tuesday evening, if all goes well and state troopers are held at bay (Curtis says his car does NOT have a radar detector), the Acura will arrive at the Four Corners area, knocking off Colorado, New Mexico and then Arizona in a frenzied few final minutes. Then it's off to a truck stop as quickly as possible. Remember, there will have been no time to shower. For more than four days.

No matter the final time, Curtis says his wife has assured him this is in fact the final time. No more such drives. Except that in July, he and Kathy and their children Sarah and Amanda will motor up to Moab, Utah, on a family vacation.

"I just like long drives," Curtis said.

Apparently so.

Getting There appears Mondays. For questions, tips or story ideas, contact Getting There at 445-3698 or bwear@statesman.com.

Find this article at:

http://www.statesman.com/news/local/see-the-usa-in-just-over-four-days-704906.html

Seeing the USA quickly

Curtis and Ray Morriss are on the road attempting to set a record for driving through each of the contiguous 48 states. This is their (carefully planned) route for doing it in just over four days.

Sources: Curtis and Ray Morriss

Robert Calzada AMERICAN-STATESMAN