Heuristics Explored: With Examples from Traffic Flow Management

Andrew J. Ryan

Overview

Chicago's Air Route Traffic Control Center (ARTCC) in Aurora, Illinois is responsible for handling aircraft arriving and departing from the world's busiest airport, Chicago O'Hare. The Traffic Management Unit (TMU) is the tactical arm of this operation, monitoring and controlling the flow of taffic going through their airspace. On a typical day, the TMU faces the challenge of feeding the appropriate number of aircraft to O'Hare and Chicago's second airport Midway, while ensuring the timely release of aircraft from the areas many satellite airports (including Milwaukee, Grand Rapids, and South Bend). Decisions made by Traffic Management Coordinators (TMC's, the workers within the TMU) can affect the entire country, yet when probed on their decision making technique, each TMC will give a different response.

While there are a defined set of rules and a priori knowledge native to all TMC's, due to the dynamic nature of their work, each TMC has their own way of employing rules in making a decision. Moreover, when presented with similar scenarios, each TMC invokes their individual heuristics, or rules of thumb, to deal with the situation. This paper attempts to examine the use of heuristics as it applies to this domain as well as the overall use of heuristics in general. The author has had the opportunity to spend over seventy hours with TMC's and considers this research key in being able to create decision support systems which make their job easier.

About Heuristics

Heuristics, which comes from the Greek *heurisken* meaning "to find," have been a topic of study since the beginning of time. Initially deemed the "art of discovery," the modern day definition of heuristics is best defined as, " . . . rules of thumb and lists of knowledge, useful (though not guaranteed) for making various selections and evaluations" (Newell 1983). Early history records show that the Pythagoreans started looking at methods of analysis in the 6th century B.C ((Hankel 1874); (Heath 1921)). In 1908, Descartes came up with twenty-one heuristics for reducing a problem. Liebniz followed up with an effort to search for a general method that would solve any problem in an algorithmic way (Groner and et al. 1983). Leibniz figured that if successful, he could create an environment where if there were arguing between people, his method would yield a resolution to any dispute!

Patrick Suppes came up with the axiomatic method in dealing with heuristics where the goal is to generate axioms that organize and facilitate thinking about a subject matter. Suppes attempted to bridge the knowledge gap that presently exists in understanding how heuristics are developed, "We are as incomplete in the formulation of heuristics as we are incomplete in the formulation of rules for learning or performing any finely tuned skill" (Suppes 1983). These represent but a few of the many empirical works on heuristics (Groot 1983) (Minsky 1983); (Tikhomirov 1983); (Wickens and Hollands 1999).

Heuristics as a Process

In "Heuristics of Cognition in Complex Systems," Dörner defines heuristics as, ". . . the science of finding solutions to problems whenever there are no algorithms." As we will later see, the domain of traffic flow management definitely fits this description. Dörner also offers the concept of a heurism: "a formula for a sequence of steps taken when working out a solution." He advises that unlike an algorithm, a heurism does not offer an a priori guarantee that a solution can be found, if one exists" (Suppes 1983). As illustrated by Descrates and Leibniz, heuristics were first developed and studied for use in well-defined areas, domains where a gold, or at least silver, standard existed – such as math. Current research attempts to break this barrier, delving into the realm of non-determinism.

General Heuristics

We use heuristics, or rules of thumb, almost unconsciously in everyday tasks. For instance, when measuring the distance of an object, we take into account the sharpness of the image. An image which is blurry is deemed to be further away than one whose representation is clear. However, this heuristic does not work when it is raining or foggy, one reason why accident reports go up under such conditions. In their seminal work, Judgment Under Uncertainty, Tversky and Khanemon list heuristics (or what they also refer to as complex biases) which affect human decision-making. Many of these heuristics will be mentioned in this paper, but the interested reader is definitely pointed toward this volume for further edification.

Why Use Heuristics?

We tend to use heuristics as cognitive shortcuts. It can be time consuming to fully evaluate each problem we encounter before making a decision. Heuristics allow us to categorize problems, their respective solutions, and come up with a solution without much cognitive effort. For instance, Chicago O'Hare's inbound traffic consists of many feeder flights[1]. Historically, these flights were small propeller aircraft whose cruising altitude was 24,000 feet. Issuing clearances for such flights was automatic since they never made it to an altitude where it would interfere with overhead traffic. Recently (partly due to the general public's negative perception of propeller driven aircraft), airlines have replaced these aircraft with regional jets which are capable of flying at 31,000 feet and above. TMC's have been slow to adapt and have found themselves in sticky situations after clearing a plane to take off and having that plane have no space in the airstream to fly. This is referred to as the hindsight bias (Poulton 1994).

[1] Feeder flights are short haul flights which deliver passengers and cargo from a remote airport (spoke) to a larger (hub) airport. This ensures that long haul flights are fully loaded, providing an economic gain to airlines.

Heuristics versus Normative Rules

Closely related to heuristics as cognitive shortcuts, heuristics are also used as substitutes for normative rules. An example of this witnessed at the Chicago ARTCC involving the prediction of a ground delay program (GDP)[2]. The forecast predicted snow and a GDP was to be enacted for the morning hours. Under optimal conditions, O'Hare can land 100 aircraft per hour. The rate was set to 40 using the heuristic that snow cuts the rate by 60%. Procedurally, there are other conditions that must be checked, including wind. As it turns out, the winds forced O'Hare into a non-optimal runway configuration, landing and departing off of one runway. Because this was not planned for, the arrival rate had to be pushed down even further, causing massive delays which extended into the next day. Here the representativeness heuristic, where people make decisions based on the ease in which the present problem matches past events, came into play and cost the airline industry tens of thousands of dollars. Figure 1 shows the gap between normative and actual judgment graphically.

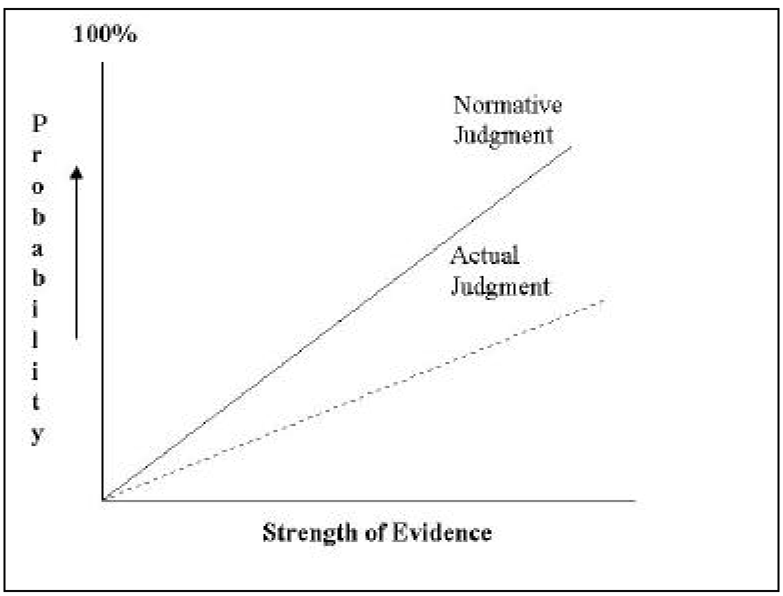

Figure 1: Normative versus Actual Judgment

[2] A ground delay program is employed when demand at an airport exceeds capacity. Enacted over a multi-hour period, a GDP sets an hourly rate at an airport that caps the number of flights which can land. Excess flights are given a delay that allows them to land at a time that the airport can accommodate them. A properly coordinated GDP can save airlines thousands of dollars as the delay is absorbed in the ground (as opposed to in the air) thus saving them fuel costs or even worse the possibility of a diversion.

In his seminal work, The Models of Man, Herbert Simon introduces bounded rationality to put theory behind the judgment gap shown in Figure 1. Bounded rationality is best described as the fact that humans cannot be expected to act rationally at all times due to cognitive limitations as well as restrictions on memory, time (how long it will take to make a rational decision) and cost (how much will it cost the user to make a rational decision as opposed to a heuristic based decision). This static view of the human mind is certainly apropos across all domains, however, there is certainly a level of specificity where a more dynamic view is needed. Gigerenzer gives us the adaptive toolbox as a metaphor for the maturation process one's heuristics go through as a result of experiential learning based on their associated cognitive abilities. The adaptive toolbox does not attempt to cover all environments in one fell swoop, instead, "[the adaptive toolbox] is designed for specific goals – domain specific rather than domain general – which enable [decision makers] to make fast, frugal, and computationally cheap decisions" (Gigerenzer 2001).

When Heuristics Go Bad

The two aforementioned TFM related examples both show what can happen when heuristics go bad. This usually occurs when decision makers do not update their heuristics with respect to time and the environment. An area where TFM struggles is feedback. Shanteau's research reveals which domains lend themselves to good decision making through feedback. Characteristics about the domain he identifies include: it is dynamic, decisions are made about things (and not people), decisions are repetitive, feedback is available, and decision problems are decomposable. Domains which fit this category include, weather forecasting, physicians, and accountants. Conversely, parole officers, stock brokers, and court judges are deemed domains where poor decisions are made – mainly due to the lack of feedback (Shanteau 1992). For TMC's, learning from experience is the prime means of avoiding the use of ineffective heuristics. However, due to the lack of feedback, they cannot always do this.

TMC's decisions affect the workload of en route controllers. Therefore, a plane which they allow to take off from South Bend's airport will eventually gain altitude and pop-up on an en route controller's radar. Depending on their workload, even a poor release by a TMC may not cause an alarm, therefore, the poor decision by the TMC goes unnoticed, thus reinforcing the poor heuristic. This result has been witnessed elsewhere as Einhorn comments, "Because of the way feedback occurs, and because of the methods we use to test rules via experience. Positive reinforcement can occur even for incorrect rules."

Such positive reinforcement leads to overconfidence. ChikGan's edited volume, *Progress in Decision Utility and Risk Theory*, examines this phenomenon by way of the calibration paradigm. This paradigm is used to answer the question: Do people know how much they know? The experiment [3] reveals an overconfidence phenomenon where people overestimate their knowledge.

A third cause for continued use of poor heuristics is the decision maker's natural tendency to not question their judgment. Wason's "2-4-6" rule induction task (Wason 1960) is typifies this occurrence. To briefly summarize the experiment: the participant is trying to guess a "rule" that classifies number triples into exemplars and non-exemplars of that rule. The experimenter provides an initial instance that conforms to the rule, and then participants propose their own instances to which the experimentor responds "yes" or "no." The first instance was 2-4-6, where the rule was "increasing numbers." Respondents guessed addition (2+4=6), increasing evens, etc. The greatest finding in the experiment is that respondents continuously generate instances of the rule they expect to be classified "yes" -- demonstrating their confirmation bias.

[3] The Calibration Method asks a subject an A or B question. The subject is asked to give a subjective probability (between 50% and 100%). They found that subjects are overconfident as their relative frequency of correct results are much less than the associated subjective probability.

Changing One's Behavior in Using Heuristics

To counteract the effects of confirmation bias and overconfidence, double-loop learning should be employed, As defined by Chris Argyris of the Harvard University Business School, "[double loop learning] allows decision makers to reflect critically on their own behavior, identify ways they often inadvertently contribute to the organization's problems, and then change how they react." Argyris makes the distinction between this and single loop learning where decision makers simply "sense and react'" instead of adding the middle step to "assess and think," an essential step in double loop learning. Periodically, decisions should be analyzed, using data mining and knowledge discovery techniques, to determine if the user is acting in accordance with their stated goals.[4] Informal interviews with Air Traffic Control System Command Center (ATCSCC) traffic flow management specialists [5] revealed that many of them could not articulate their desired goals when issuing a ground delay program. This result falls in line with the research of Argyris, "Ask people in an interview or questionnaire to articulate the rules they use to govern their actions, and they will give you what I call their 'espoused' theory of action. But observe these same people's behavior and you will quickly see it has very little to do with how they actually behave." Double loop learning will keep the user more in tune with their goals and even provide guidance if they begin to make decisions that are not in harmony with their stated goals.

Another means to correct heuristics is training. Considered the best way to debias a decision maker, training allows the decision maker to calibrate their responses before having to act in a real-world situation. Mistakes can be made, lessons learned, and a ground truth established, before having to perform on their own. Fischoff writes, "[A] variety of training efforts have been undertaken with an admirable success rate . . . some of the more necessary conditions for learning seems to be: receiving feedback on large samples of responses, being

[4] The field of knowledge discovery in databases has drawn much interest in its goal of extracting knowledge from static databases. An excellent primer on this subject is: Advances in Knowledge Discovery and Data Mining by Fayyad et al.
[5] Interviews were conducted with various level employees at the ATCSCC facilities in Virginia. The ATCSCC is the center for all traffic flow operations in the nation.

told about one's performance (and not just about common problems), and having the opportunity to discuss the relationship between one's subjective feelings of uncertainty and the numerical probability responses" (Fiscoff 1982). One caveat in using training is the fact that the trainer can influence the subject's decision making to the point where they are no longer acting naturally.

Finally, there is learning direction theory (Selten and Stoecker 1986; Selten and Buchta 1999), which offers a quantitative measurement of how far off one is in their decision making, which creates a baseline for successive attempts to close the gap. Learning direction theory is best explained through analogy: Consider an archer who repeatedly aims to hit the trunk of a tree, if he misses to the right, he aims his next attempt a bit closer to the left. He is given feedback and aided by the qualitative model of his environment (the tree), and is able to draw an informed conclusion of which direction a better alternative can be found (Selten 2001). Armed with these facts, we now examine how the Federal Aviation Administration (FAA) prepares its controllers for dealing with the fast paced environment of traffic flow management (TFM).

Training in the FAA

The FAA does not allow a controller to work on their own until they become certified. Until that point, the controller will work alongside a certified controller who would take over if needed. On one hand, this allows a controller to ask questions and learn from their trainer, but it also prevents them from forming their own identity as a controller. They never learn how to escape from a hazardous situation because as soon as it gets to that point, the trainer will diffuse the problem. Trainers are instructed to let the situation develop as far as humanly possible before stepping in, but the ultimate responsibility rests with the trainer so a quick hook is not uncommon (Hoffman 2002). Eventually, the trainee becomes certified and begins to form their identity as a controller. The first step is developing personal (as opposed to those adopted from their trainers) heuristics. The next section discusses some obstacles in changing/modifying one's heuristics – the very process the newly certified controllers will undergo.

Factors which work against Changing Heuristics

Overconfidence was mentioned as one factor leading to the continued use of poor heuristics. Another aspect to be considered is the use of anchors when making decisions, and more broadly, probability in general. Anchoring occurs when people make estimates starting from an initial value that is then adjusted (without using normative rules) to yield a final answer. An example of anchoring occurs when asking people to multiply 1 x 2 x 3 x 4 x 5 x 6 x 7 x 8 versus 8 x 7 x 6 x 5 x 4 x 3 x 2 x 1. Here, subjects tend to look at the first few numbers and perform those computations and extrapolate the product from that initial estimate. Naturally, both expressions yield the same product: 40,320, however when stated in ascending order, the median estimate was 512, and for descending order, 2,250 (Tversky and Kahneman 1982).

Anchoring is based on an individual's inability to adjust their heuristics when probability changes. The availability heuristic speaks to this and is defined as, "the situation in which people assess the frequency of a class or the probability of an event by the ease in which instances or occurrences can be brought to mind" (Tversky and Kahneman 1982). This author fell prey to this heuristic in believing that there was little, to no, airplane traffic at night. However, a weather specialist quickly pointed out that all of the delivery couriers fly at night, creating a decent amount of traffic along with red-eyes.[6]

A more serious example involves a controller who is new to the job or is working an abnormal (say nighttime) shift. Unconsciously, they make decisions based on the knowledge they have accrued from their routine work tasks. Failing to take into account the new realities of a different shift, they may under/over estimate some variable based on their regular shift experience.

[6] Red-eyes are cross country flights which operate at night.

Who can Use Heuristics?

We use heuristics from birth. A baby's main goal is survival, to survive it needs food, therefore they invoke the heuristic that anything that can fit in their mouths must be edible, and therefore will advance their survival. As time goes on, they refine this heuristic, ultimately learning that everything that fits in their mouth is not food. This type of heuristic maturation bodes well with the laws of nature, we learn as we grow, "If people learned and continue to use poor rules, does this not contradict the evolutionary concept of 'Survival of the Fittest'" (Einhorn 1982)? The question then becomes, is it simply age (and in the same breath education) which nurtures more mature use of heuristics?

Heuristics and Age/Education

David Klahr performed a study where third graders, sixth graders, community college students, and university students were asked to solve a problem. Klahr's goal was to examine how age and scientific training influence difference in domain general heuristics used to constrain search in the experiment space. He concluded that the focusing heuristic, the ability to hone in on a singular variable and make changes to only that variable, was the main difference across abilities. Each group eventually solved the problem, with the more advanced students taking less time than the less advanced students. Yet, the third graders took a more sporadic approach, seemingly jumping from alternative to alternative in a non-systematic manner. Conversely, the university students were able to focus on a single variable, make incremental changes in value, and hone in on the correct solution.

Finally, Klahr's most robust finding centered around the participant's ability to confirm their initial hypothesis. Studies show that adults attempt to confirm, rather than disconfirm, their current hypothesis ((Gorman 1989); (Klayman and Ha 1987). However, Klahr finds that for implausible hypotheses, adults and children used different strategies. Adults tended to pose hypotheses from different frames to conduct experiments that could discriminate between the two, while children proposed a different frame which made the initial hypothesis feasible, and then ignored the initial result (Klahr 2000). We will revisit this result for adults once we begin to talk about heuristics and TFM. In the interim, the literature offers some definitions of heuristics which compliment Klahr's findings.[7]

Simon offers the notion of weak methods (or heuristics). Weak methods are defined as, "[Heuristics] which require little knowledge of the problem structure for their application, but are correspondingly unselective in the way in which they search through the problem space" (Simon 1983).[8] There are five types of weak methods:

1. Generate and test – trial and error (the third graders were guilty of this)
2. Hill climbing – make several moves, the one which advances you the most, you choose and repeat
3. Means and analysis – Compare the current state and goal state and produce a description of which differences exist. Then search for an operator that can reduce those differences (Newell and Simon 1972) (Dunker 1945).
4. Planning – create an abstract version of the problem, solve the abstract version and use the plan used to solve the abstract problem to solve the original problem (Newell and Simon 1972).
5. Analogy – Mapping between a new target domain and a previously encountered base domain.

The use of weak of heuristics, while time saving, often leads to non-optimal results. For the most part, subjects tend to take experiences from other domains and use these weak heuristics to find similarities and correlations which will help them solve the problem at hand. The lack of experiences for the younger subjects is a prime factor in their taking a long time to solve the problem using weak heuristics, while the other subjects had more experience to draw on.

---

[7] To bring closure to the question of do the continued use of poor heuristics defy "Survival of the Fittest," the answer is no. Since being the *fittest* involves a relative ordering, while optimal implies an absolute level, the continued existence of sub-optimal rules does not contradict Darwinian theory (Einhorn, 1982).

[8] Conversely, a strong method is one which requires expertise in the area and allows solutions to be found with minimal search.

Heuristics and Problem Solving

Thus far, we have spoken about the use of heuristics in problem solving. Herbert Simon takes this one step further and looks at discovery and problem solving. He pontificates, “Much of scientific reasoning consists of forming new concepts – via induction – on the basis of experimental evidence” (Simon 1977). At its core, problem solving involves searching problem spaces, and heuristics are shortcuts employed to decrease the search time. However, author Conan Doyle, of Sherlock Holmes fame retorts, “It is a capital mistake to theorize before one has data.” There is a fine line between intuition, which Holmes seemed to employ, and heuristics. The difference being a covert arrogance in the belief that one’s intuition is too complex to be considered a generic heuristic. There is really no difference besides the fact that a heuristic can be shared, while intuition cannot.

George Polya, considered the founding father in the study of heuristics, offers three assumptions when examining the role of heuristics in problem solving:

1. Heuristics means “serving a discovery”
2. Solving a problem certainly contains a bit of discovery, hence it involves the heuristic process
3. Investigation into heuristics cannot aim at finding infallible rules [9] of how to make discoveries; it is directed at comprehension of human problem solving principles. (Cellerier 1983)

Polya’s hypothesis cannot be refuted. The connection between problem solving and heuristics is certainly evident in our everyday lives. The next section will examine heuristics in decision making, including the inductive and deductive characteristics involved – attempting to identify how heuristics are learned.

[9] Descartes and Liebwitz would most certainly be disappointed.

Learning from Experience

Heuristics and Induction

Induction, or the concept of drawing conclusions from specific events and using those inferences on universal cases, definitely plays a role in the nature of learning from experience. One must create a categorization system to be able to apply the proper heuristics in the required situation, "If heuristics are learned through induction, it is necessary to group tasks by similarity or else there would be as many rules as situations" (Einhorn 1982). Yet, people tend to do a poor job of organizing their experiences. Those who are scientifically inclined are actually trained to group similar experiences (i.e. theorems, formulas), but Einhorn remarks, "Much of professional training teaches people to recognize problems as belonging to a class of problems having a given structure and (sometimes) known solution" (Einhorn 1982). At this point, it should be noted that the FAA's minimum standards for being a controller are three years of college or three years of work experience. They have recently begun targeting graduates form aviation programs from colleges, however the aging rate of the FAA's controller population definitely shows that most of their current workforce entered the workforce under the earlier rules.

Heuristics and Deduction

Optimal rules, such as Bayes theorem, are learned deductively. However, such rules are, by their nature, abstract and context independent. This leaves it to the human decision maker to decide when and how to apply these rules. For this reason, machines are sometimes better decision makers than humans.[10] It has been well documented that humans are not optimal decision makers, "A human being is not an exact measurement device producing quantitative measurements. This is the reason for intransitive behavior in problems of

[10] Appendix A compares the human decision maker to the modeled (automated) decision maker.

choice“ (Gal and et al. 1997). However, research shows that humans may not perform as poorly as has been suggested.

The way information is presented definitely plays a role in how the decision maker perceives it. For example, data presented via a pie chart is more understandable than the same data listed, unordered, via text on a computer screen. Gigerenzer and Hoffrage extend this idea to the use of heuristics. They argue, ordinary people’s Bayesian reasoning can be improved and cognitive illusions eliminated when information is presented in frequency formats (Gigerenzer and Hoffrage 1995). The basic concept is that information presented via single cues, (i.e. ‘600 out of every 1000 males who plays 10 or more hours of video games will need glasses’ or ‘100 of every 1000 males wear glasses’), can be stored in the decision maker’s memory and allow nesting of cues to offer solutions for new problems, “How many of the males coming into the office who play 10 or more hours of video games will need glasses?” The retrieval of the first two cues, surely makes this problem more straightforward than the true Bayesian representation.[11]

To date, there have been no successful applications of aviation technology which incorporate bounded rationality and optimal decision making. The high task complexity of traffic flow management leads to a heavy reliance on heuristics.

The goal here is to create a deterministic mechanism to allow a decision maker to choose from a set of possible choices with minimal cognitive effort. White offers us programmed selection, “[which] applies to classes of well-defined repetitive problems and is carried out by a well-defined decision rule which determines which action will be taken in any problem of the class” (White 1969).

[11] For more on this topic, see Krauss et al.

Heuristics and Traffic Flow Management

Traffic flow management (TFM) can certainly be defined as a well defined repetitive problem yet there is a great deal of disparity between how TMC's do their job. One of the disadvantages of creating rules which allow for programmed selection is that one must ensure that the decision made is identical to the decision which would have been made without the use of formal aides. Otherwise, the decision maker is not learning, the "system" is performing the cognitive work for them. We will not go into the formulation of an actual system in this paper, but it is surely an interesting problem to see if such a system is possible. In the meanwhile, TMC's are besieged with a bevy of systems to make their job easier. Naturally, they have adopted heuristics to suit their needs. The next section will examine these heuristics, how they were formed, and the differences between coordinators. First a brief overview of TFM.

About TFM

Since 1960, air passenger traffic has increased at an average yearly rate of 9% [Donohue and Laska]. Because of this steady increase in demand, the airways have become increasingly more congested. While congestion in the airways is easy to deduce form this scenario, another entity, the airport, is also affected. In its purest form, it is easiest to envision a flight in three stages: take-off, en-route, and landing. The airport dominates two of these three components and for that reason plays a large role in how traffic flows across the National Airspace System (NAS). Accordingly, the Federal Aviation Administration (FAA) has two separate organizations to monitor these functions. Air traffic control, which ensures safe separation between aircraft, and traffic-flow management (TFM), which balances demand and capacity to maintain safe and efficient traffic flow (Chang and et al. 2001). TFM is tasked with the responsibility of minimizing the interruptions to the NAS, so that the available capacity is utilized by existing demand. When demand exceeds capacity, they must make decisions and take actions to create an optimal situation for NAS users. Figure 2 depicts the two branches of air traffic management.

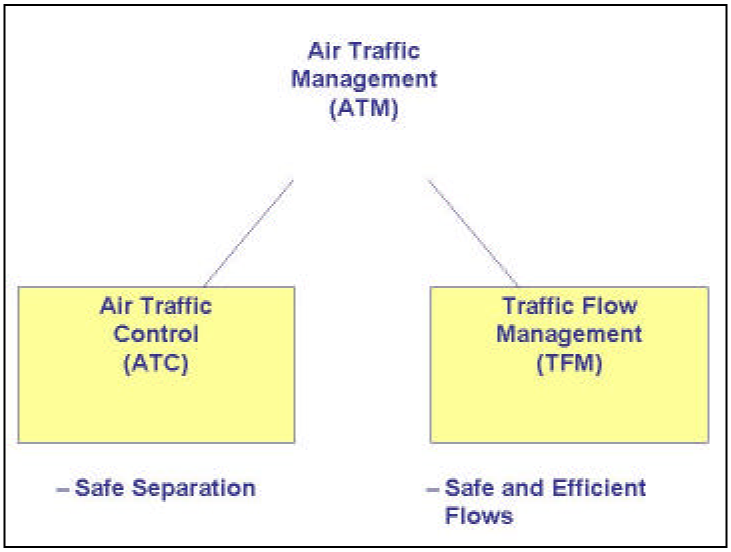

Figure 2: Areas of Air Traffic Management

Site Visit to Chicago's Air Route Traffic Control Center

In support of this research, on Friday, April 19, 2002, the author visited Chicago's Air Route Traffic Control Center, in Aurora, Illinois,[12] to interview members of their traffic management unit. As described above, the main tasks of the traffic flow coordinators (TMC) is to, " . . . balance air traffic demand with system capacity, to ensure efficiency in the utilization of the total National Airspce System; thereby producing a safe, orderly, and expeditious flow of traffic, while minimizing delays"(FAA 1997). There are many different positions involved, and

[12] The question may arise to why Chicago's ARTCC (ZAU) as opposed to the Washington ARTCC (ZDC) which is in Virginia. Due to the sensitive nature of the airspace which ZDC controls, a trip to their facility was not allowed. Luckily, previous acquaintances (special thanks to Maurice "Mo" Hoffman), ZAU welcomed my visit and the TMC's were all very helpful in donating their time to assist my research. Mike O'Brien who is in charge of the facility should be commended for his outstanding leadership as ZAU runs a tight operation!

each TMC, over time, will become trained for all of them. The positions which I focused on were the arrivals and departures desks.

The Departures Position

O'Hare International Airport (ORD) is the busiest airport in the United States. ORD is the main concern of TMC's at ZAU. The departure desk coordinates ORD departures from area airports (there are many small airports in ZAU including Green Bay, Milwaukee, and South Bend) into ORD or other large airports.[13]

Their main concern is the overhead traffic, and being able to release a flight for take-off, near its departure time, while being able to find an open space for the flight once it reaches cruising altitude. Some of the heuristics involved here are:

1. A jet (when cruising) will travel between seven and eight miles a minute.
2. Runway configuration at airport XXX will add XXX minutes of time to the flights ascent towards cruising altitude
3. A release will need a 20 mile hole to enter overhead stream

All TMCs agree, that these heuristics are all based on experience, and not science. Yet, their performance is still solid. It is amazing to watch the TMC's work as there is very little physical calculation done. Their main tool is the Traffic Situation Display (TSD), and via this spatial representation, they are able to draw conclusions and make decisions. The next section will describe how different TMC's perform the task of releasing a plane from the departures desk.

The Arrivals Position

The arrivals position coordinates arrivals into ORD. This is a very important position because their actions affect the entire NAS. During peak

[13] Newark, LaGaurdia, and JFK normally top the list of airports which require care from TMC's.

periods, ORD can land up to 100 planes, but once that max is reached, ZAU has very little free airspace to perform traffic management initiatives, like vectoring, metering, miles-in-trail, or circular holding. Instead, these duties are passed back to neighboring centers. This means that once the TMC realizes that the flow into ORD is too heavy, they must call other centers and ask them to hold or space out planes headed toward ZAU. This often sets off a chain reaction where the effect can be felt on both coasts. The next section will examine how this determination is made.

While TMC's have a wide array of decision support tools to aid in their judgment, they mostly rely on good-old-fashioned radar. With a sweep of about eight seconds, a controller's ability to make good spatial decisions, usually overrides any type of automation they have available to them. Figure 3 depicts the ZAU airspace during a typical AM rush. There are heavy flows from the north and southeast. The picture shown here is very similar to the Traffic Situation Display (TSD) which all controllers have.

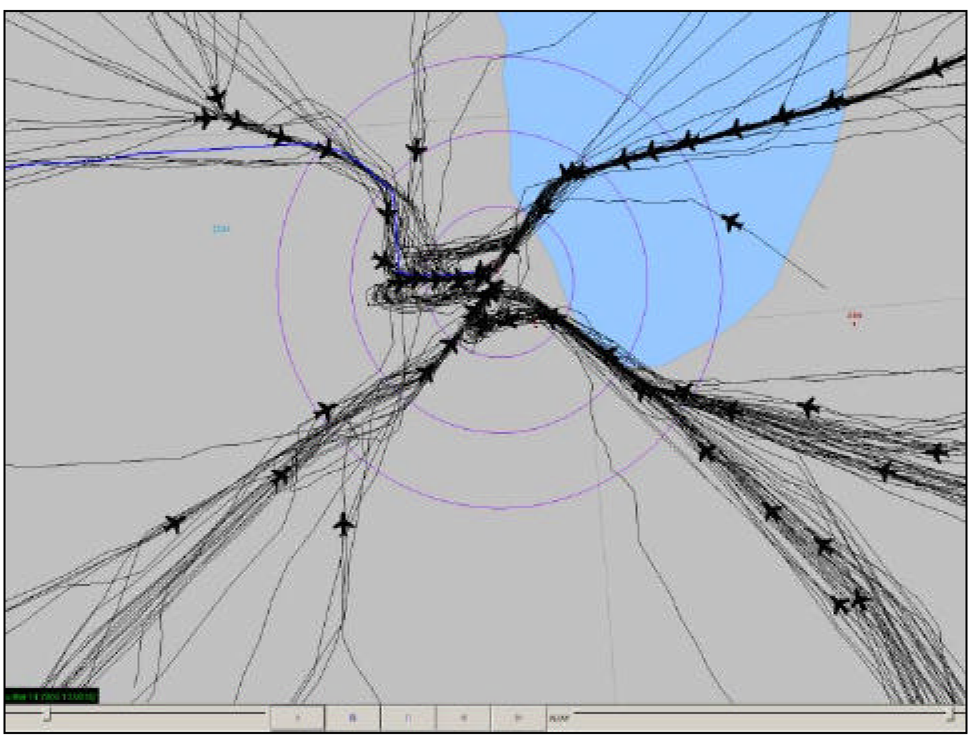

Figure 3: Chicago O'Hare Incoming Traffic at 1300Z on March 14, 2002

The big advantage of TSD is the spatial view it gives the user. Another tool in the field is the Flight Schedule Monitor (FSM). FSM (depicted in Figure 4) serves as a situational awareness tool between the airlines, the FAA operational centers, and the ATCSCC. It contains real-time updates on airline schedule changes, reroutes, delays, etc. According to controllers, its main drawback is that it does not match the paradigm they are used to, that is it does not allow them to use their heuristics.

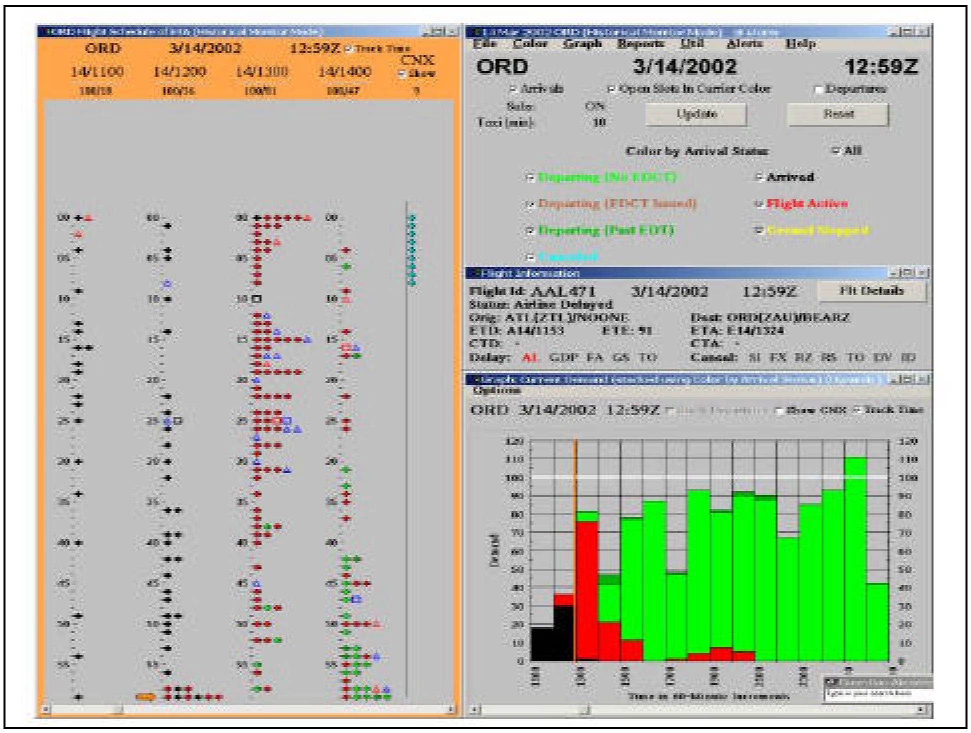

Figure 4:Flight Schedule Monitor Depicting O'Hare Airport

For instance, as illustrated in Figure 3, controllers are able to determine when a traffic initiative (i.e. miles-in-trial, airborne holding, metering[14], or vectoring). Visual heuristics also allow TMC's to determine if planes can be offloaded to another side of the airport (i.e. a plane which was scheduled to

[14] Due to the limited amount of airspace in ZAU, they do not use metering and rarely employ airborne holding.

arrive on the northeast can be swung over to the northwest – actually evident in Figure 3). Factors involved in this decision include, the time of day, the volume of departures[15], and the airline involved. Intuitively, TMC's generate a list of scenarios where a traffic management initiative would be successful. Falling prey to the availability and representativeness heuristics, if the current situation matches previous scenarios, they will employ the TMI. Otherwise, they would simply ignore it. Their thinking can be best summed up as "If it worked yesterday, it will work today."

Due to the culture of the FAA, this type of mentality actually ensures job security. Controllers have very low turnover rates and excellent salary.[16] The charter of the FAA (and hence the controllers) is safety; pushing the envelope by attempting to make optimal, as opposed to routine decisions, does not fall within this scope. However, there are ever changing conditions in the NAS which do cause TMC's to adjust their thinking.

The Move from Propellers to Regional Jets

As described above, ZAU departures coordinates flights departing from satellite airports. This section will focus on flights departing from satellite airports coming into ORD. Historically, airlines flew cost-efficient propeller planes for the short flight. This made releasing planes fairly routine as propeller planes (props) fly lower than jets and thus do not have to be mixed into the same airstream. In the last few years, regional jets (forty to seventy seat jets) have begun to replace props. This change was more a function of the general publics disdain of props as opposed to an economic decision. For TMC's, it meant the nearly automatic release of a plane was now replaced with queries into what type of plane it was,

[15] Chicago O'Hare is a true corner post facility. Planes arrive from the NE, NW, SE, and SW, and depart from the N, S, E, W. During a heavy departure period, it would be impossible to cross a plane from the NE to the NW due to the departure traffic headed out to the north.
[16] The average salary for an air traffic controller is in the low six figures, and the normal workday consists of a rotations of shifts and breaks where a controller will spend about five hours "on duty" over the course of a eight hour shift.

which runway it was taking off from, and anticipated taxi-time. The additional cognitive workload in making this once routine decision will undoubtedly lead to the invention of a new heuristic for this scenario. According to Maurice Hoffman, a TMC at ZAU, they still get caught off guard as they expect a prop and not a jet. This pain is passed on to the en-route controller who then has to blend the "supposed" prop into the jet's airstream. Often the mistake is not even recognized as the en route controllers quietly absorb the hidden jet without complaint.

While this type of teamwork helps keep the system functioning, it also fosters an overconfidence bias. There is no feedback loop which allows TMC's to witness their errors and take corrective action. We have already noted that decision makers tend not to look for negativity in their decision making and in this, and other scenarios, a confirmation bias takes place, creating an artificial air of perfection for TMC's.

This author has written a paper, "Improving Decision Making via Knowledge Management" on the use of knowledge management in TFM to help alleviate this problem. The paper suggests that the "collective wisdom" within the FAA should be leveraged to provide controllers with a greater knowledge base when making decisions. Currently, individuals make decisions based on their experiences, which reflect a small percentage of the whole. Via knowledge management, a holistic view of the system can be captured and disseminated to all controllers by way of a decision support tool (Ryan 2001). The premise of the paper holds as all of the TMC's interviewed agreed that they share heuristics among each other and have faith in their colleagues. Seamster et al. share this belief as they remark, "[Heuristics] may be learned during training, passed down from others, or developed as personal rules through experience."[17] Experience generally has the most lasting effect as the person is able to internalize the

[17] Being well versed in Black history, the author could not resist but to point out the similarity between Seamster's statement and the 1967 words of Black Panther leader Huey Newton, "There are three ways one can learn: through study observation and experience."

environment, how they felt, what the scope of the heuristic is, and most importantly *when* it should be invoked.

Conclusion

Heuristics are ubiquitous in everyday life. This paper attempts to highlight the various uses of heuristics, how they are developed, when they are used, and how they can be trained to yield better results. The theme of traffic flow management was interspersed throughout the paper to enable the reader to witness heuristics employed in a practical setting. Unlike the deterministic domains, such as math and science, which heuristic approaches were initially fashioned, traffic flow management is a more dynamic field. One notable difference is the temporal aspect of traffic flow management. Due to the strict time requirements, TMC's do not have the luxury of thoroughly thinking through a problem before responding. Moreover, they rarely have the time to reflect upon past decisions before moving on to the next. Imagine a mathematician solving a problem, and then being asked to solve a similar problem without knowing if the first were correct! This is the world TMC's live in everyday.

The key to effective heuristics is proper feedback and the ability to incorporate the lessons learned into future decisions. Currently TMC's are left to their own devices to do this. It is imperative that future technologies be enabled with functions which assist them in this task. As technology continues to remove cognition from the human, and place more of the onus on the computer, heuristics begin to play a bigger role in the overall interaction between the human and machine. While the technology becomes an increasingly important aspect in aviation, so does the reliance on heuristics by the operator to yield the expected results. It is imperative that the use of heuristics become part of the system development process, thus closing the gap between human expectations and the performance of the technology.

Bibliography

Cellerier, G. (1983). Guidance of Action by Knowledge. Methods of Heuristics. et al. Hillsdale, Lawrence Erlbaum and Associates.

Chang, K. and et al. (2001). "Enhancements to the FAA Ground Delay Program Under Collaborative Decision Making." International Journal of the Institute for Operations Research and the Management Sciences **31**(1).

Dunker, K. (1945). "On problem solving." Psychological Monographs **58**(5): 270.

Einhorn, H. J. (1982). Learning from Experience and Sub-optimal Rules in Decision Making. Judgement Under Uncertainty: Heuristics and Biases. A. Tversky. Cambridge, Cambridge University Press.

FAA (1997). ZAU TMU Traffic Management Unit Briefing Packet. Aurora, FAA.

Fiscoff, B. (1982). Debiasing. Judgement Under Uncertainty: Heuristics and Biases. A. Tversky. Cambridge, Cambridge University Press.

Gal, T. and et al., Eds. (1997). Multi Criteria Decision Making Advances in MCDM Models, Algorithms, Theory, and Applications. Boston, Kluwer Academic Publishers.

Gigerenzer, G. (2001). The Adaptive Toolbox. Bounded Rationality. R. Selten. Cambridge, MIT Press.

Gigerenzer, G. and U. Hoffrage (1995). "How to improve Bayesian reasoning without instruction: Frequency formats." Psych. Rev. **102**: 682-704.

Gorman, M. E. (1989). "Error, falsification and scientific inference." Quarterly Journal of Experimental Psychology **41**(A(2)): 385-412.

Groner, R. and et al. (1983). Aopproaches to Heuristics: A Historical Review. Methods of Heuristics. et al. Hillsdale, Lawrence Erlbaum and Associates.

Groot, A. D. D. (1983). Heuristics, Mental Programs, and Intelligence. Methods of Heuristics. et al. Hillsdale, Lawrence Erlbaum and Associates.

Hankel, H. (1874). Zur Geschichte der Mathematik in Alterthum und Mittelalter. Leipzig, Tuebner.

Heath, T. L. (1921). Greek Mathematics Vol. 1. Oxford, Clarendon Press.

Hoch, S. J. and H. Kunreuther, Eds. (2001). Wharton on Decision Making. New York, John Wiley & Sons.

Hoffman, M. (2002). Personal Communication. A. J. Ryan. Chicago.

Klahr, D. (2000). Exploring Science: The Cognition and Development of Discovery Processes. Cambridge, MIT Press.

Klayman, J. and Y. Ha (1987). "Confirmation, disconfirmation and information in Hypothesis testing." Psychological Review **94**: 211-228.

Minsky, M. at al. (1983). Jokes and the Logic of the Cognitive Unconscious. Methods of Heuristics. Hillsdale, Lawrence Erlbaum and Associates.

Newell, A. (1983). The Heuristic of George Polya and Its Relation to Artificial Intelligence. Methods of Heuristics. et al. Hillsdale, Lawrence Erlbaum and Associates.

Newell, A. and H. Simon (1972). Human Problem Solving. Englewood Cliffs, NJ, Prentice-Hall.

Newton, Huey P. "The Correct Handling of a Revolution." Black Panther Newspaper July 20, 1967.

Poulton, E. C. (1994). Behavioral Decision Theory. New York, Cambridge University Press.

Ryan, Andrew J. Improving Group Utility in the Collaborative Decision Making Process. October 10, 2001 2001. Research paper. George Mason University. Available: http://classweb.gmu.edu/ajryan/gdm.pdf.

Selten, R. (2001). What is Bounded Rationality? Bounded Rationality. R. Selten. Cambridge, MIT Press.

Selten, R. and J. Buchta (1999). Experimental scaled bid first price auctions with directly observed bid functions. Games and Human Behavior. et al. Hillsdale, NJ, Erlbaum.

Selten, R. and R. Stoecker (1986). "End behavior in sequences of finite prisoner's dilemma supergames." J. Econ. Behav. Org **7**: 47-70.

Shanteau, J. (1992). "Competence in experts: The role of task characteristics." Organizational Behavior and Human Decision Processes **53**: 252-266.

Simon, H. (1977). Models of Discovery. Dordrecht, Reidel.

Simon, H. (1983). Understanding the processes of science: the psychology of scientific discovery. Progress in Science and Its Social Conditions. T. Gamelius. Oxford, Pergamon: 159-170.

Suppes, P. (1983). Heuristics and the Axiomatic Method. Methods of Heuristics. et al. Hillsdale, Lawrence Erlbaum and Associates.

Tikhomirov, O. K. (1983). Informal Heuristic Principles of Motivation and Emotion in Human Problem Solving. Methods of Heuristics. et al. Hillsdale, Lawrence Erlbaum and Associates.

Tversky, A. and D. Kahneman (1982). Availability: A Heuristic for Judging Frequency and Probability. Judgment Under Uncertainty: Heuristics and Biases. A. Tversky. Cambridge, Cambridge University Press.

Tversky, A. and D. Kahneman (1982). Judgment Under Uncertainty: Heuristics and Biases. Judgment Under Uncertainty: Heuristics and Biases. A. Tversky. Cambridge, Cambridge University Press.

Wason, P. C. (1960). "On the failure to eliminate hypotheses in a conceptual task." Quarterly Journal of Experimental Psychology **12**: 129-140.

White, D. (1969). Decision Theory. Chicago, Aldine Publishing Company.

Wickens, C. and J. Hollands (1999). Engineering Psychology and Human Performance. New York, Prentice Hall.

Appendix A: Comparing Experts and Models in Decision Making Tasks

(Hoch and Kunreuther 2001)

Where Models Excel and Experts Fail	Where Experts Excel and Models Fail
Bias	*Subjectivity*
➢ Experts are subject to bias of perception and evaluation while models are deterministic in their interpretation of a problem	➢ Experts are proficient at attribute-valuation and provide evaluations of variables that are difficult to measure objectively. Models can only operate on the data provided.
Overconfidence	*Granularity*
➢ Experts suffer from overconfidence and may be influenced by organizational politics that encourage strategic responses; models are immune to social pressures for consensus	➢ Models know only what the expert tells the model builders; experts know what questions to ask and can garner further information if needed.
Vigilance	*Flexibility*
➢ Experts get tired, bored, and emotional, models do not	➢ Experts have highly organized, domain specific knowledge. They may have superior pattern matching skills which allow them to recognize and interpret outliers, while models tend to omit these cases.