Fuzzy Adaptive Path Evaluation for Intelligent Route Guidance Systems

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ABSTRACT

Advanced communication technologies and computer-based systems are shaping the design of traveler information systems. The next generation of route guidance systems will likely feature artificial intelligence components that are better capable of responding to individual driver's needs. This paper presents a fuzzy reasoning approach to path evaluation that would be an important component in a next-generation dynamic route guidance system. As a multiple-objective approach, this fuzzy path selector aims to improve the realism and marketability of in-vehicle route guidance systems. An example is provided to demonstrate the potential for using fuzzy adaptive models to make route guidance systems more responsive to a driver's needs and preferences.

Keywords: Route guidance, traveler information systems, and fuzzy logic

1. INTRODUCTION

Adler and Blue (1998) posit that next generation traveler information systems, termed Intelligent Traveler Information Systems (ITIS), will emerge from the synthesis of Advanced Traveler Information Systems (ATIS) and artificial intelligence (AI). These next-generation systems will be capable of providing travelers with more personalized, user-specific information. Among the features that will distinguish ITIS from ATIS include: (a) the ability to recognize the user and respond directly to the users needs and preferences, (b) natural language processing and real two-way voice communication, (c) capabilities for the system to learn and adapt to changes in the network and changes in user preferences and behavior, and (d) intelligence to proactively scan available information sources to generate dynamic route guidance based on prevailing and anticipated network conditions. ITIS will also be ergonomically designed to minimize driver overload and improve travel safety.

In-vehicle route guidance systems (IVRGS) are among the core ATIS technologies. IVRGS are in-car devices designed to assist drivers with wayfinding and navigation. Among the perceived benefits of IVRGS include shorter travel times, reduced stress, and more effective pre-trip and en-route decision making. Although currently the user cost of these technologies is high and most systems cannot yet provide real-time guidance, development progress is rapid. Within a decade, the technology will mature and many vehicles will likely be equipped with some type of IVRGS.

One of the major challenges to advancing IVRGS is the integration of intelligence and making the devices more user friendly. Tarry (1996) states that private companies have understood that they must build devices that cater to individual driver's needs. They have begun to develop ITS that reduce the adverse effects on individual drivers but may not be of benefit to the whole network. Field studies have demonstrated that drivers perception of IVRGS would become more favorable if the systems were more intelligent. Schofer et al., (1997), as part of the ADVANCE ITS demonstration project, reported that people who tested in-vehicle route guidance systems wished to have more control over the route planning and be able to set their own criteria, even multiple criteria. It was also suggested that enabling route guidance systems to learn and adapt to the driver's route choice behavior would be desirable.

To be perceived as being driver-specific these "more intelligent" route guidance systems will be better able to incorporate driver preferences, more flexible in developing routing strategies, and adapt to changes in both driver behavior and the traffic network. There is a clear indication that travel time and cost do not always dominate the route selection process (Golledge, 1993). Choice factors that influence path selection typically relate to one of four categories: the perceived available routes, the character of the traveler, the trip to be made, and other circumstances (Bovy and Stern, 1990). Travelers commonly trade-off travel time to select routes that are more direct, more scenic, untolled, or bypass neighborhoods perceived to be dangerous. The depth of drivers' spatial knowledge of the roadway network, including the layout, orientation, and congestion conditions, has a direct impact upon how drivers make route choices (Golledge, 1993). Drivers who have a greater familiarity with network conditions and network layout should be expected to make more efficient pre-trip route choices as well as be able to better adjust their travel pattern en-route in the presence of severe congestion. Experiments by Adler et. al., (1993) suggested that previous experiences with the current and alternate routes also influence route switching.

IVRGS need the ability to elicit routing preferences from users and apply this knowledge in formulating a multiple-objective path search problem. Furthermore, since drivers' route choice behaviors are based on their spatial knowledge, it would be beneficial for IVRGS to take this into account when developing and providing route guidance assistance to the driver.

This paper presents a fuzzy logic-based approach of path evaluation for a core subsystem of a next-generation ITIS-based dynamic route guidance system. The purpose is to provide a mechanism for incorporating driver knowledge and judgement within route guidance systems to ensure that the system is capable of providing advice that is consistent with a particular driver's travel objectives and routing preferences. The formulation is an extension of previous work by Adler (1993,4) and also builds off of other well-known models.

The order of the paper is as follows. The next section discusses Adler's two-stage model of en-route choice behavior. This is followed by a discussion of why a fuzzy adaptive approach for path evaluation is appropriate for intelligent dynamic route guidance systems. Description of the model and an example of its application within intelligent route guidance systems are then presented.

2. THE TWO-STAGE EN-ROUTE BEHAVIORAL MODEL

En-route behavior has been characterized as an iterative process in which drivers are constantly assessing the current state of the travel process and adjusting their behavior in response to changes in the system (Ben Akiva et al., 1991, Khattak et al., 1993, Adler et. al., 1994,). Models are sought that can predict the conditions under which drivers consider adjusting their en-route behavior, typically in the form of path switching or modifying the travel goals based on updated information.

Striving to meet travel objectives is also an essential part of travel planning and route selection (Bovy and Stern, 1990). Drivers are seen as being goal-oriented and path choice, both pre-trip and en-route, is made with respect to achieving these travel goals. A similar theory is that changes in en-route behavior stem from drivers' reaction to increased frustration and anger at deteriorating travel conditions (Khattak et al., 1993; Adler et. al 1994). Diversion behavior can be predicted using a threshold model that measures increased difference between perceived and expected travel conditions.

Adler et al., (1993 and 1994) conceptualized a two-stage model of en-route driver behavior based on some fundamental behavioral theories developed in the areas of psychology, social science, and human choice behavior. It is assumed that while en-route, drivers are constantly assessing and reevaluating their current route and their travel objectives with respect to the prevailing and anticipated conditions on the network. Adler's conflict approach represents a two-stage decision making process. The first stage focuses on the assessment of the current path. As the driver moves through the network the current path is assessed. If the driver is satisfied with the performance (experienced and anticipated) of the current path, there is no consideration given to switching. However, if the driver believes that the current path will not enable him to satisfy the travel objectives, a decision to switch to an alternate path will be considered. Gateways for defining potential alternate paths occur at intermediate nodes in the network, called here 'decision nodes'**.**

The second stage of the behavioral model focuses on alternate route identification and evaluation. If the driver perceives an available alternate path from the nearest decision node to the destination, an assessment of the relative improvement over the current route is taken. If the driver believes that the alternate path is more attractive than the current path, a decision to switch paths will be made. There is an implied strength of association between current path satisfaction and motivation to divert. The less satisfied a driver is with the current path, the more likely he is to switch paths, even for lower relative improvement.

3. CONCEPTUALIZATION OF THE PATH EVALUATION SYSTEM

Fuzzy logic is a methodology for applying common sense rules that refer to indefinite quantities. It provides computer modeling logic that reaches beyond the capabilities of conventional mathematical models to emulate human decision making. Fuzzy systems can systematically manipulate vague inputs and model the resulting decision making process. They are particularly good at modeling behaviors that are rule based and lack a definite mathematical model (Kosko and Isaka, 1993).

In the context of path selection, drivers' decisions are often made based on vague interpretations of network attributes. Traditionally drivers have difficulty relating to exact values of path attributes like travel time and complexity. For example, we would not expect drivers to state that if the expected travel time of Path A is less than 34 minutes, it will be selected but at 35 minutes Path B will be chosen. Rather, drivers often rely on heuristics. For example, a path may be selected because it has a low travel time, limited number of turns, and for the most part consists of highway links.

Fuzzy logic is appealing because it provides for handling vagueness within a rule-based approach. Koutsopoulos and Lotan (1993) used fuzzy logic and approximate reasoning to model route choice behavior. Pang et al., (1995) applied a fuzzy-neural approach to model driver route choice to complement the implementation of in-vehicle dynamic route guidance systems (DRGS). Driver preferences were represented by a fuzzy expert system and the driver's reaction to the advice provided by the DRG system is stored. The fuzzy-neural approach is adaptive in that the system is trained on real decisions and actions taken by the driver. The approach presented here differs in that it treats each alternate path independently and does not perform direct comparisons in performance. Within this work the driver is provided a ranking of paths that are thought to match the driver's profile. Actual notions of path switching are not directly handled by Pang's system.

The fuzzy logic formulation presented in the next section is based on the two-stage approach discussed earlier. The first is current path assessment -- how drivers assess the prevailing conditions on the current path to determine if remaining on this path can satisfy the travel objectives. The second is path switching -- the comparison of the current path to the best alternative path to determine if it is worthwhile to switch paths.

3.1 Fuzzy Logic Approach

The framework for developing path evaluation routines that capture the essence of Adler's two-stage model of driver en-route behavior is based on the concept of a ***fuzzy controller.*** The two-stage formulation is akin to a control system in which the current conditions are always being monitored and decisions to make adjustments to the current scheme are undertaken if necessary. Fuzzy controllers are special types of expert systems that combine a knowledge base (expressed as a set of fuzzy inference rules) and an inference engine used to solve the problem. Measurement inputs from a real-world process are collected and converted into fuzzy sets through fuzzification. The fuzzified measurements are processed through the rule base to evaluate control strategies. The results are defuzzified and appropriate actions are taken on the real-world process. The design of the fuzzy control system involves 6 steps (based on Klir and Yuan, 1993)

1. ***Identifying relevant input and output variables***: For the en-route switching problem the set of inputs are those variables that are determinants of route choice, such as travel time, out of pocket cost, route complexity, and so forth. The outputs for our model are the level of conflict arousal and motivation to divert.

2. ***Assigning Linguistic states:*** After selecting the input and output variables, each one must be formulated into a set of linguistic states and expressed by fuzzy sets.

3. ***Introduce a 'fuzzification function' for each input variable*****:** This function represents the associated measurement uncertainty.

4. ***Develop Fuzzy Inference Rules:*** The set of inference rules dictates the control logic to be followed. Typically these rules are generated in one of two ways - either by eliciting them directly from the human user or operator or by studying empirical data and applying learning methods, like neural networks.

5. ***Inferencing:*** Combining measurements of the input variables with information rules to make inferences regarding the output variables. All rules are fired in parallel and to some degree.

6. ***Defuzzification:*** Convert the generated conclusions of the inference, denoted by a fuzzy number, back into a single real number. Several methods for defuzzification, including '**center of area method'** and '**center of maxima method'** have been developed and applied.

A more detailed and generic explanation of fuzzy controllers and fuzzy set theory can be found in many sources, including Klin and Yuan (1993); Kosko (1993), and Kosko and Isaka (1993).

The two-stage approach focuses on the sequential nature of the choice process. During the first stage, the driver assesses performance on the current path and as travel conditions worsen, there is an increase in motivation to divert. Based on the degree to which the driver is motivated to divert, alternative paths are identified. The best alternate path is compared with the current path to determine if path switching would significantly improve the likelihood of satisfying the travel objectives. The next two sections describe the adaptive fuzzy formulation of the path evaluation algorithm that captures the essence of the two-stage behavioral model.

Stage #1 - Estimating Driver's Level of Conflict Arousal

For the presentation of the model it will be assumed that en-route travel decisions are evaluated based on two path criteria – '*travel time*' , expected travel time from origin to destination and '*trip complexity*' - a 'catch-all' category for capturing activities that impact the safety of traffic operations and comfort of the driving task. Paths having high complexity might include several road changes (lots of turns), permissive left turns at busy intersections, interactions with pedestrians, maneuvering through complex merging/weaving movements. It can also represent travel on a path with unstable flow conditions resulting in 'stop and go' conditions and requiring constant braking/accelerating behavior. The travel time objective reflects a driver's attitude toward the perceived travel conditions on a path. It is used as an indicator to measure the degree to which the perceived travel conditions on the current path meet (or exceed) the driver's expectations. Motivation to consider alternate paths is influenced by perceived and anticipated travel time on the current path. Since path complexity is typically better understood by drivers and exhibits less variation, it has less of an effect on path switching but plays an important role in pre-trip and en-route path evaluation.

The first stage of the algorithm represents a process by which the IRGS relates driver response in light of existing traffic conditions. Fuzzy reasoning is incorporated to model the conflict arousal associated with assessing performance of the current path. Figure 1 illustrates how the variable "**Travel Time** " is decomposed into four linguistic states and represented by fuzzy sets. The four states represent levels of performance defined in relationship to the driver's expectations: **E** (Excellent) - corresponding to travel conditions that are better than expected, **G** (Good) corresponding to conditions within expected ranges, **F** (Fair) representing conditions below expectations, and **P** (poor) corresponding to conditions that exceed a tolerance and would cause the traveler not to select that route under any circumstances. This fuzzy representation would be used for a single origin-destination pair or a single path alternative. These sets are shown as trapezoids but it could be determined that other shapes would better satisfy the representation scheme.

For each state associated with the linguistic variable there is a membership curve to define the fuzzy restrictions, also known as the membership set for a specific variable. Fuzzy curves are used to map a linguistic state between values of 0-1, indicating a degree of membership. Using expected travel time as our variable, we are interested in mapping values of travel time to the linguistic states. Figure 2 illustrates how the inputs and outputs are patched through a set of fuzzy inference rules. On this figure, travel time (on the x-axis) is mapped against conflict arousal (on the y-axis) and an example of a resultant inference rule is depicted for the state of having a fair travel time. A scale of 0-100 is introduced to represent the degree of diversion motivation; 0 indicates there is little motivation to leave the current path and 100 percent indicates that the driver is extremely interested in considering alternate path options.

The fuzzy inference engine and associate rule base provide the means by which the inputs are mapped to the outputs. For the relationship illustrated in Figure 2 there are four inference rules to be fired simultaneously upon receiving a value for the input variable travel time:

Rule 1: IF the *travel time* is *Excellent* THEN *Motivation* is *None*
Rule 2: IF the *travel time* is *Good* THEN *Motivation* is *Low*

Rule 3: IF the *travel time* is *Fair* THEN *Motivation* is *Moderate*
Rule 4: IF the *travel time* is *Poor* THEN *Motivation* is *High*

Once a value is computed for the input variable, all of the rules will be fired in parallel. Depending on the value of the input variable, one or more of the rules will fire at a level above 0% and the rest at 0%. For example, a travel time of 30 minutes will fire rule 2 at 100% and the others at 0%. However, a travel time of 42 minutes will fire rule 3 at 80% and rule 4 at 30%. A method of interpolation is applied whereby a weighted average of all fired rules is sought. This is depicted in Figure 3.

The conclusion, initially expressed in terms of a fuzzy set, is then defuzzified to obtain a result expressed as a single real number. The most frequently used defuzzification method for simple fuzzy controllers is the centroid method. This method was adopted for this work.

The resulting centroid of the combined areas generated by the rules that fire with probability > 0% becomes the computed diversion motivation value DM. This value is compared to a stated threshold Ψ. If DM $\geq \Psi$ then the inference moves to stage 2; otherwise, no action is taken.

For two criteria, the set of inference rules is expanded but the fundamental process is not changed. Considering travel time (T) and complexity (C) as inputs, the inference rules for diversion motivation (DM) can be expressed as:

If T = a and C = b then DM = c

Or for short <T = a, C = b; DM = c>

An example rule would be:

IF travel time = *excellent* and complexity = *fair*

THEN diversion motivation = *moderate*

Figure 4 represents a crisp representation of an inference rule base mapping for the two input variables. The crisp representation assumes that it is known with certainty which set each input belongs to. However, as illustrated above, there are situations where the driver's operating condition will have a probability of belonging to more than one input fuzzy set. In fact, the current route may have two values for both travel time and complexity. This causes several of the above rules to fire with differing intensities.

The intensity with which a rule fires is computed using the standard fuzzy intersection: For a rule (T=a, C=b, DM=c) the rule fires at intensity R(t,c) given as:

$$R(t,c) = \min\,[P(T), P(C)] \qquad (1)$$

DM is then computed using a weighted area approach. For i rules that fire with probability greater than 0%:

$$DM = \frac{\sum_i (A_i * C_i)}{\sum_i (A_i)} \qquad (2)$$

Where A_i is the area and C_i is the centroid for rule i.

Stage #2 - Assessing Route Switching Behavior

As the level of diversion motivation increases, the desire to switch paths intensifies and the amount of improvement in goal attainment needed on the alternate path decreases. The boundedly rational switching model, discussed by Mahmassani and Jayakrishnan (1991), establishes a useful framework for comparing two paths. The model formulation is given as:

$$\delta_j(k) \quad = 1 \text{ if } TTC_j(n) - TTB_j(n) > \max(\eta_j * TTC_j(n), \tau_j) \qquad (3)$$

$$= 0 \text{ otherwise}$$

For driver j, $\delta_j(k)$ is a binary variable where 1 indicates a route switch; 0 no switch at node n. $TTC_j(n)$ is the anticipated (or instantaneous) trip time from node n to destination on current path. $TTB_j(n)$ is the trip time for the best alternate path. The sensitivity for the switching rule is controlled by η_j, representing a relative indifference threshold based on the fraction of the trip remaining and τ_j, the minimum improvement needed for a switch. The latter two parameters ensure that drivers do not switch paths for very small perceived improvements in travel time and relate the savings to the remaining trip time.

In this form, the boundedly rational model has two potential weaknesses for use within IRGS. First, the model is limited to cases in which minimizing travel time is the single objective. Second, the model as stated also does not directly account for strength of diversion motivation away from the current path.

We propose an extension of the model that handles multiple criteria and directly incorporate the output of the conflict arousal variable as an input to the second stage. The IRGS works on the assumption that the likelihood of a driver wanting to switch paths is based upon the potential improvement in goal attainment of the alternate path in comparison to the current path. The likelihood is also a function of the degree of diversion motivation. As motivation increases, the driver is willing to switch paths for a lower rate of improvement. If utility is defined to measure the perceived worth of a path the decision criteria can be written as:

$$\delta_j(k) \quad \begin{aligned} &= 1 \quad \text{If } DM * (U_{b,j}(k) - U_{c,j}(k)) > \tau_j \\ &= 0 \quad \text{otherwise} \end{aligned} \tag{4}$$

In this equation DM represents the level of diversion motivation for the current path taken as the output of the first stage of the decision model. U_b and U_c represent the perceived utility (scaled between 0 and 1) based on multiple criteria for the best alternate (U_b) and current routes (U_c) respectively. τ represents a minimum improvement in utility that must be achieved. This formulation is consistent with the original boundedly rational model. Adding the DM term on the left side relates the difference in perceived utility to the diversion motivation factor. Low values of DM will force the model against diversion.

Specifying Fuzzy Relations Relative to Network Performance

In our path evaluation model, all pre-trip routing and en-route switching decisions are based on a comparison with expected conditions on a set of best paths through the network. Figure 5 illustrates a template that might be used by an intelligent DRGS to evaluate paths for a commuter. The two charts illustrate the fuzzy memberships for this commuter's preferences toward expected path travel times and complexity. To estimate the ranges for path travel time and complexity, we have adopted an approach whereby the DRGS searches for some 'K' best non-dominated paths between the vehicle's current position and destination. The numbers for travel time and complexity generated by these K-best paths are used to establish the baseline for the x-axes. This approach is demonstrated in the example that follows.

4. EXAMPLE FOR INTELLIGENT ROUTE GUIDANCE SYSTEMS

This section describes the application of the path evaluation model for a commuting trip. A test network was extracted from actual the roadway network in the vicinity of Anaheim, California. Consider the case of a commuter whose car is equipped with an IRGS. The commuter is assumed to have a solid understanding of the roadway network, and in general, has little tolerance for delay. To appropriately represent this driver's preferences, the fuzzy input sets, shown as Figure 5, have specific characteristics. Only travel times around the system mean can be considered excellent or good. As the network performance degrades slightly, his dissatisfaction level is likely to increase quickly. In terms of complexity, given the nature of the trip, the commuter is more likely to endure paths with higher complexity if they have lower travel times. This is reflected in the figure by a wider excellent state for average weighted complexity. The commuter's vehicle is assumed to be equipped with a route guidance system able to receive real-time data on link travel times and volumes and is capable of computing shortest paths based on the two objectives. The driver is also assumed to fully comply with the system.

The test network, shown in Figure 6, consists of 22 nodes and 35 links and includes freeway segments, major arterials, and local streets. Lengths are measured in meters, mean speeds in meters per second, and average link travel times in seconds. The mean speeds are assigned based on facility type with freeway links having the highest mean values. Standard deviations are randomly generated also based on facility type. Complexities are assigned in the range of [1..5] based on the facility class, expected volumes and densities, variance in travel speeds, interchanges to enter and exit the link (freeway-freeway, freeway-arterial,…) with movements between roadway classifications having higher values. Table 1 provides a list of the link attributes and values of expected travel time and complexity representative of historical performance.

Expected path travel times and complexities are computed by adding the mean values of the links that constitute the path. For purposes of the storyboard and computing path variances we assume that the links are independent so that the path variances for travel time and complexity can also be determined by adding across the links[1].

This commuter is assumed to make routing decisions based on the two objectives, minimizing travel time and minimizing route complexity, with the former having a greater value. The

[1] It is recognized that this is a restricting assumption because in reality links are dependent and the variance of the sum of non independent random variables is the sum of the variances plus the covariance. However, since the sum of the variances themselves is a lower bound on the true path variance, larger variances in travel times can be expected. The independence assumption simplifies the modeling process, and does not invalidate the example.

driver's route choice behavior is modeled by the fuzzy mapping of travel times and complexities to four linguistic states as described earlier. The resulting set of 16 inference rules is shown in Figure 4. For this commuter, the right hand side of the rule set was developed to give more weight to the travel time objective. Equal weighting of the two criteria would produce a symmetric rule set.

The motivation to divert is depicted by the fuzzy sets in Figure 7. The x-axis represents a level of diversion motivation, computed as the output of the first stage of the model. The y-axis represents the degree of membership in the three fuzzy states ("weak", "moderate", "strong") scaled between zero and one. For this example it is assumed that the route guidance system has learned the driver's tolerance to congestion. A threshold value (Ψ) of 0.6 is adopted for this example, meaning that when the diversion motivation exceeds 0.6, the IRGS believes that the driver is motivated enough to actively consider an alternate route. For values below 0.6, the IRGS believes that the driver may be frustrated with the current path but not significantly motivated to consider switching paths.

Pre-Trip Route Selection

Upon starting the trip, the route guidance system employs some multiple-objective search routine to identify the set of non-dominated paths based on a combination of real-time and historical data. Such a multiple objective path algorithm is presented in Blue, et al. (1996) and Adler and Blue (1999). Expected path travel times are computed as the sum of the average link travel times over all links along the path. Average path complexities are computed as the weighted average of link complexities taken over the total length of the path. For this network there are two non-dominated paths for conditions listed in Table 1: O-1-4-13-14-15-16-D having expected travel time in seconds, average weighted complexity of (563, 2.0) and O-1-2-3-9-12-20-D having (619, 1.26). The first path is more direct but uses a greater percentage of arterial and local streets. The second path is longer but includes mostly freeway links.

From a set of k-best paths (dominated and non-dominated) generated from the data set, the system estimates a mean and standard deviation of path travel times and complexity. For this example k = 10 was used and this yielded mean travel time in seconds and complexity of (664, 2.2) respectively. The associated standard deviations are (66, 0.5). These computed mean values are used as reference values for the fuzzy sets, essentially establishing the relative ranges on the 'x' axis of Figure 5.

The selection of the initial route computes route utility in a way that will be treated in the discussion of the second part of the two-stage model. The route guidance system computes the utility of each path from the fuzzy sets where the "good" range is centered at the mean values. Figure 8 indicates the mapping of the non-dominated paths to the fuzzy states. Path 1 is selected as the initial path choice as it has excellent travel time and good complexity

Decision Phase #1 – Current Path Assessment

As the driver sets out on the selected path the current conditions in the network are being monitored by the system. There are two sets of travel time and complexity values that will influence the behavior: the values from the origin to the current location, $(t,c)_{o,l}$ and the expected values from the current location to the destination $(t,c)_{l,d}$.

Consider the case when the driver starts out on the selected route and passes node 1 after 78 seconds, this is larger than the expected time of 64 seconds but not large enough to induce a change in behavior. However upon entering arc 1-4 the level of congestion suddenly increases on the current path and new network data is collected by the system. The expected travel time and complexity values based on historical data for arc 1-4 is (61.0, 1.0) but the route guidance system, taking into account real-time data, generates a revised estimate of (120.0, 1.5).

From a behavioral perspective, the driver will experience delays on this link and, based on his experience, will attempt to assess how severe this congestion. The driver will become motivated to consider switching to an alternate path if the congestion is anticipated to be severe enough to cause significant delays and increased difficulty to the driving task. However, without real-time information the decision is made under uncertainty. The driver can compare the perceived conditions against historical experiences. Due to the inherent variability in travel times in a network, it is possible that the driver previously experienced this level of congestion on this link multiple times but each corresponded to a different network-wide congestion pattern. The driver is forced to consider one or more possible scenarios and make an educated guess as to which scenario is actually being played out in the network.

A route guidance system capable of receiving real-time information can assist the driver by directly computing expected travel times and prescribing an appropriate course of action. An “appropriate” action is one that is consistent with how the driver would respond if he is making decisions based on perfect information.

From the model’s perspective, the first action is to assess the current performance relative to historical data. Figure 9 illustrates the application of the first phase of the behavioral model, assessing the performance along path 0-1-4. The expected values of travel time and complexity for this path based on historical data are (125, 2.0) with standard deviations of 45 and 0.2. These revised estimates (210, 1.5) are also highlighted on the figure. When the 210 seconds is mapped against the fuzzy sets, the system concludes that the current path from the origin to node 4 has an 45% likelihood of belonging to a fair travel time and a 17% chance of belonging to a poor travel time. Because the observed complexity is nearly the minimum complexity, the observed complexity of 1.5 has a 100% association with the excellent set.

The rules that fired with probability greater than 0% have intensity computed by equation 1:

R(T = F, C = E; DM = P) = min(0.45, 1.00) = 45%

R(T = P=, C = E; DM = S) = min(0.17, 1.00) = 17%

The mapping of the output, diversion motivation, is shown in Figure 10. The level of diversion motivation can be quantified by defuzzification, calculating the combined centroid of the resulting areas. The centroid of the <T=F, C=E; DM = P> rule is 0.5, with an area of 0.135. The centroid of the <T=P, C=E; DM =S> rule firing is 0.814, with an area of 0.060.

The resulting value of diversion motivation computed from equation 2 is:

$$\mathrm{DM} = \frac{((0.060 * 0.814) + (0.135 * 0.500)}{(0.060 + 0.135)} = 0.60$$

This computed value is then compared with the stated threshold to determine whether the system should move to phase two and consider alternate paths. For this case, the computed level of diversion motivation is 0.60 and it is compared to the stated threshold of 0.60. The system will begin to scan the network for alternate routes branching off the current path at the next available interchange. The computed level of diversion motivation will be used during Phase 2 to evaluate potential alternate paths.

Decision Phase #2 – Path switching

The route guidance system moves to the second phase of the model and begins to search for the best alternate path to the destination originating from the next intersection (node 4). A comparison between the current path and the best alternate path is performed to determine if the driver would benefit significantly from switching paths. As explained in the pre-trip planning section, these two paths will be evaluated with respect to the prevailing average conditions on some k-best paths from the current location to the destination.

Based on updated values of network volumes and travel times, the route guidance system can compute a new expected travel time and complexity to the destination on the current route. It can also scan the network for alternative paths. Consider the case in which the updated travel time, complexity pair for the current route is (750, 3.3) and for the best alternate path, identified as 4-5-6-7-10-15-16-D, is (657, 3.7). Based on the k = 8 best paths from 4 to D, expected values of travel time and complexity are (685, 4.0) with standard deviations of 82 and 0.8.

The mean travel time and complexity values of the k-best paths are again used to set the limits on the ‘x’ axis of the fuzzy input sets for the driver. The mean travel time value becomes again the center of the fuzzy good range, and each fuzzy set is defined around the standard deviation. Figures 11 and 12 illustrate the mapping for the current and best alternate paths. For the current route, the travel time belongs 14% to “good” and 48% to “fair”. Average weighted complexity belongs 19% to “excellent”. The alternate route's travel time belongs 25% to “excellent” and 60% “good”; the average weighted complexity belongs 50% to “good”.

These input performances are mapped to fuzzy association sets for route utility. Route utility is characterized as the inverse of diversion motivation; high utility corresponds to low diversion motivation. A set of 16 inference rules is generated to link travel time and complexity to route utility. For this example, Route Utility was depicted with four linguistic groups: Excellent, Good Fair and Poor. Figure 11 graphically shows the Route Utility rule set. To quantify the Route utility, a fuzzy output map for Route Utility is shown in Figure 12.

Like in Phase 1, the rules that fire above 0% are combined to generate areas whose centroids are then computed. Equation 1 is used to compute the firing intensity. For the current route, the <T=G, C = E; U = G> rule fires with an intensity of 0.14; the <T=F, C=G; U=F> rule fires at 0.19. For the alternate route, the <T=E, C=G; U=G> rule fires at 0.25; <T=G, C=G; U=G> rule fires at 0.60. These firings are shown in Figures 13 and 14 respectively.

Using equation 2 to find route utility leads to U_c (current) = 0.55 and U_b (Best Alternate) = 0.80. These values are substituted into the revised boundedly rational model, described by equation 4, to determine if the alternate path provides significant improvement that would induce the driver to switch paths. Assuming a minimum improvement value of $\tau = 0.10$, representing a 10% improvement in route utility, and using DM = 0.60 from Phase 1, the modified boundedly rational model is applied and in this case, the system would advise the driver to switch paths.

$DM^*(U_b\text{-}U_c) > \tau$

$0.60^*(0.80\text{-}0.55) > 0.10$

0.15 > 0.10 -- **Switch Paths**

DISCUSSION AND CONCLUSIONS

This paper presented an approach for dynamic path evaluation based on fuzzy logic. This system, derived from Adler's two-stage conflict arousal model of en-route driver behavior, is designed for third generation intelligent dynamic route guidance systems. The evaluation procedure includes a two-stage review process. In the first stage of the model, the system collects information regarding the prevailing conditions on the current path, relative to the whole network, and uses fuzzy reasoning to determine if the driver's travel goals and objectives are not being met. In the second phase, the best alternate path is identified and compared against the current path, again considering the prevailing and anticipated performance of the network. A modified boundedly rational approach is used to relate the level of conflict arousal to the motivation of switching paths. If the system concludes that the alternate path is likely to provide significant improvement in route utility, the driver will be advised to switch paths.

The formulation provides a hybrid approach that extends and combines previously developed models and ideas. It is posited that applying fuzzy inference would enable a route guidance system to better respond to a driver’s routing preferences and eliminate potential conflicts or compliance problems. The proposed two-stage route assessment approach is well suited for DRGS because it seeks to find routing solutions that satisfy driver's personal routing preferences and needs. Furthermore, this approach provides a direct mechanism for relating strength of diversion motivation to path switching decisions.

Although the example focused on bi-objective path search and a single user, the framework of the path evaluation system presented here is generic and designed to be amenable to a wide range of driver classes and route choice criteria. Changes in the model's variables, such as shapes of fuzzy input functions, diversion motivation threshold (DM) , and minimum utility improvement index (τ), can be used to model different driver classes. Casello (1997) presents a multi-class example to demonstrate how three driver classes (commuters equipped with ATIS, non-equipped commuters, and tourists) could be modeled with the same framework.

Providing the route guidance system with the necessary calibrated parameters poses the greatest challenge. Pang (1995) demonstrated the ability to use neural networks for enabling learning and adapting. Work is underway to develop an adaptive version of the system that would be capable of learning driver behavior. Work is also planned to calibrate the model for certain driver classes. Previous simulation experiments have yielded insights as to how drivers state travel objectives and adapt their behavior while en-route. Additional in-laboratory simulation studies will be undertaken to further study driver route choice behavior.

The use of a k-best path strategy to derive normative network conditions is also a topic for further study. There are several algorithms that can generate k-best paths based on multiple objectives. Work is needed to determine how best to apply these algorithms. First, we intend to undertake simulation experiments to study how 'k' should be treated, namely how many paths should be sought to provide the baseline. It is likely that 'k' would be a function of the network as well as the preferences of the driver. Second, there are several ways to identify "best paths". We have generally assumed that multiple-objective non-dominated paths would be used to compute the baseline conditions. It may be prudent to consider distinct best paths (as discussed by Scott et al., 1997 for example).

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Table 1. Initial Network Attributes

From Node	To Node	Length	Mean Speed	Avg. TT	Variance	Avg. C
0	1	1590	25	64	24	0
1	2	3200	25	128	32	1
2	3	3860	25	154	39	1.5
3	9	2170	25	87	22	1.5
1	4	1530	25	61	23	1
2	5	1060	20	53	16	1.5
3	7	1120	20	56	17	2
4	5	1170	20	59	18	2
5	6	1610	20	81	24	2
6	7	2650	20	133	40	4
7	8	530	20	27	8	4
9	8	800	20	40	12	4
4	13	3140	25	126	47	2
6	14	1770	14	126	57	1
7	10	1370	20	69	21	5
8	11	1530	14	109	49	4.5
9	12	1535	25	61	15	1
10	11	885	14	63	28	3
12	11	645	14	46	21	2
10	15	1160	20	58	17	4
11	16	1480	14	106	48	4
12	20	1850	25	74	18	2
13	14	1320	14	94	42	2
14	15	2300	18	128	58	2.5
15	16	1095	18	61	27	3.5
13	17	1125	25	45	17	1
14	18	480	14	34	15	4.5
15	19	615	20	31	9	4.5
16	D	400	14	29	13	4.5
17	18	320	14	23	10	2
18	19	2170	14	155	70	3.5
19	D	3170	14	226	102	4
20	D	710	14	51	23	2
17	21	2320	25	93	35	1
21	19	1320	20	66	21	2

Figure 1: Linguistic Representation for Travel Time Performance

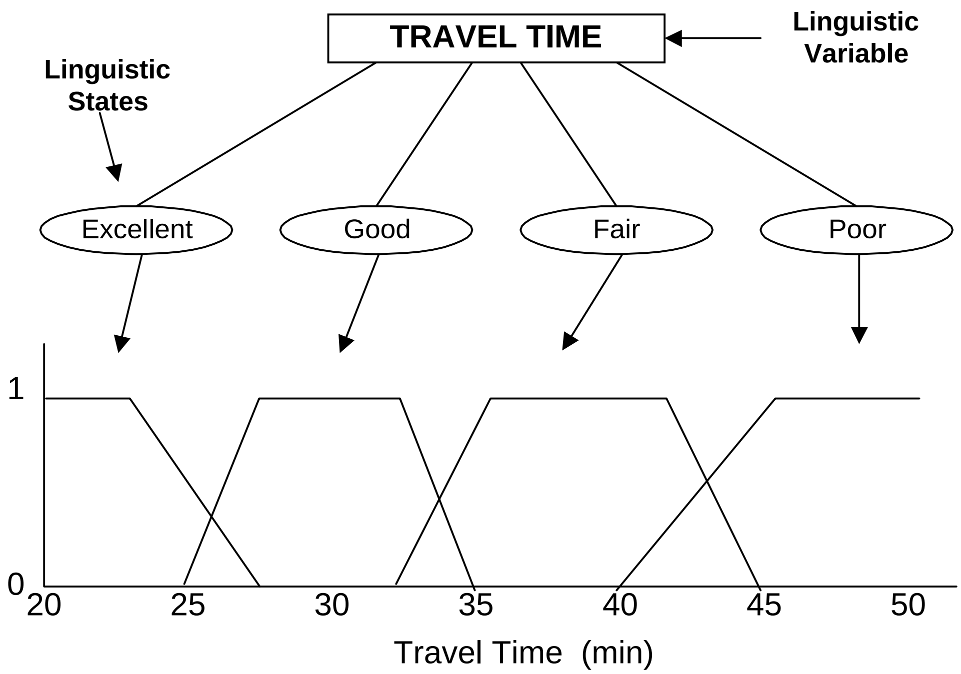

Figure 2: Patching Inputs to Outputs Through a Rule Base

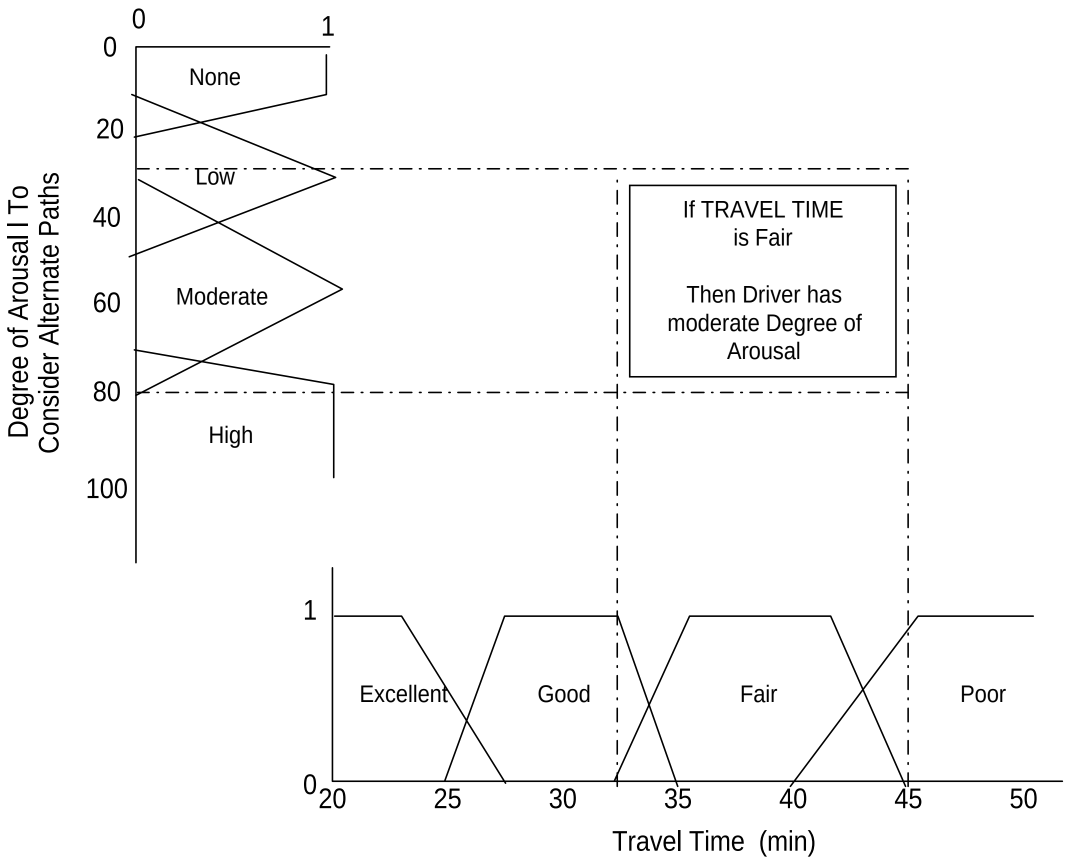

Figure 3: Firing the Rule Base

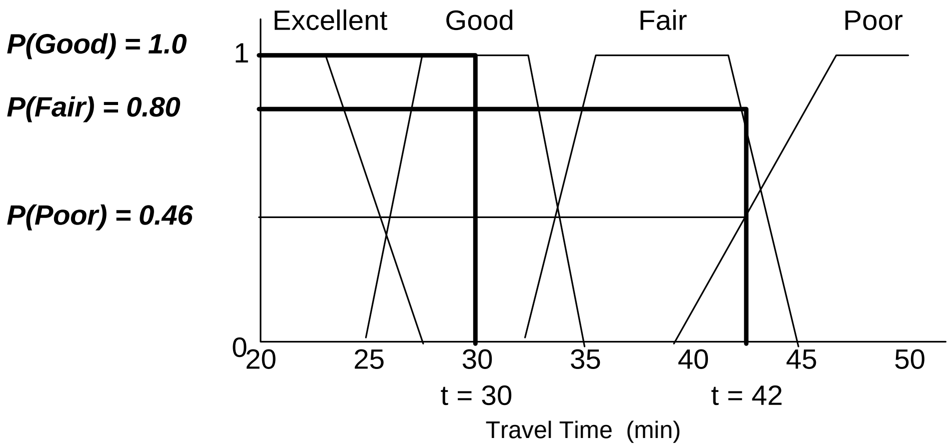

Figure 4: Fuzzy Rule Base for Diversion Motivation

Complexity

		E	***G***	***F***	***P***
	E	W	W	M	M
Travel	***G***	W	W	M	M
Time	***F***	M	M	S	S
	P	S	S	S	S

E = Excellent; G = Good; F = Fair; P = Poor
W = Weak; M = Moderate; S = Strong

Figure 5: Behavioral profile for Commuter with DRGS

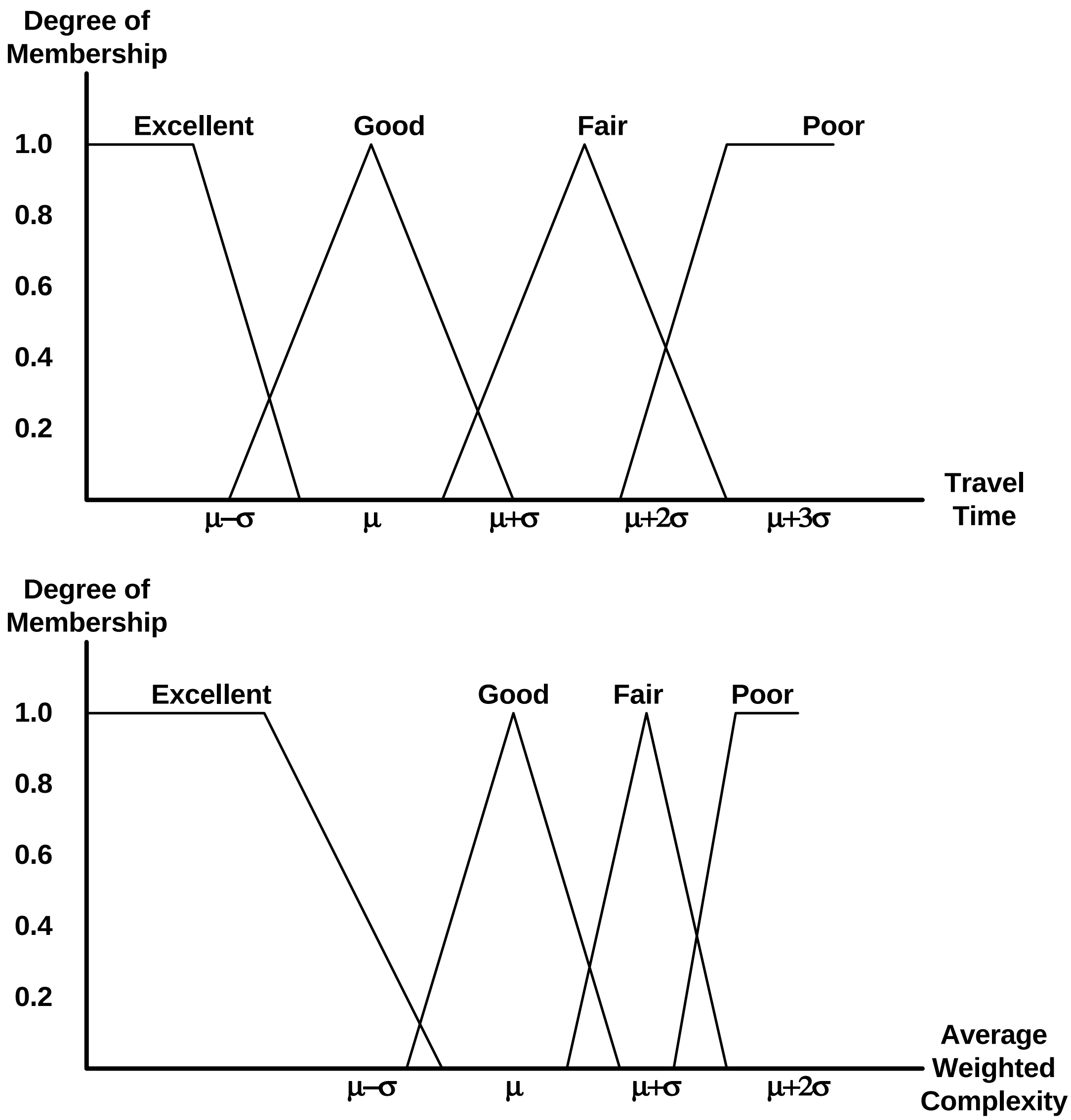

Figure 6: Test Network

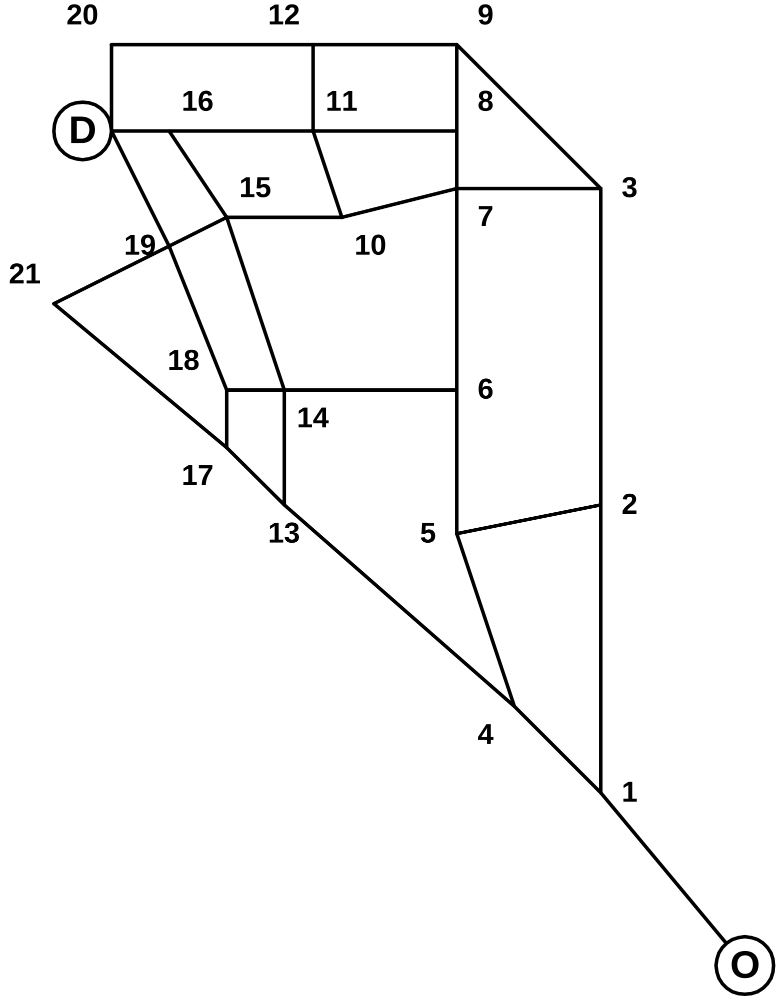

Figure 7: Mapping Diversion Motivation

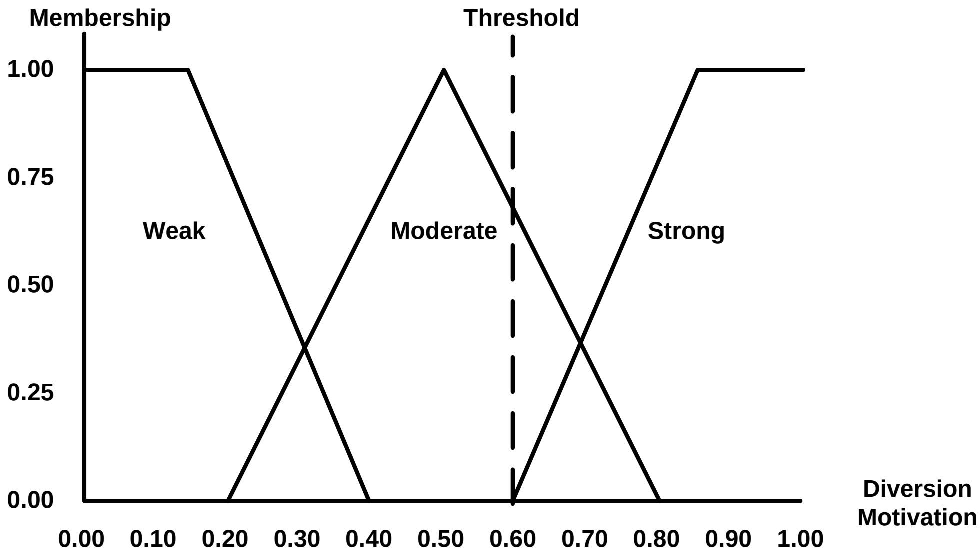

Figure 8: Pre-Trip Route Selection

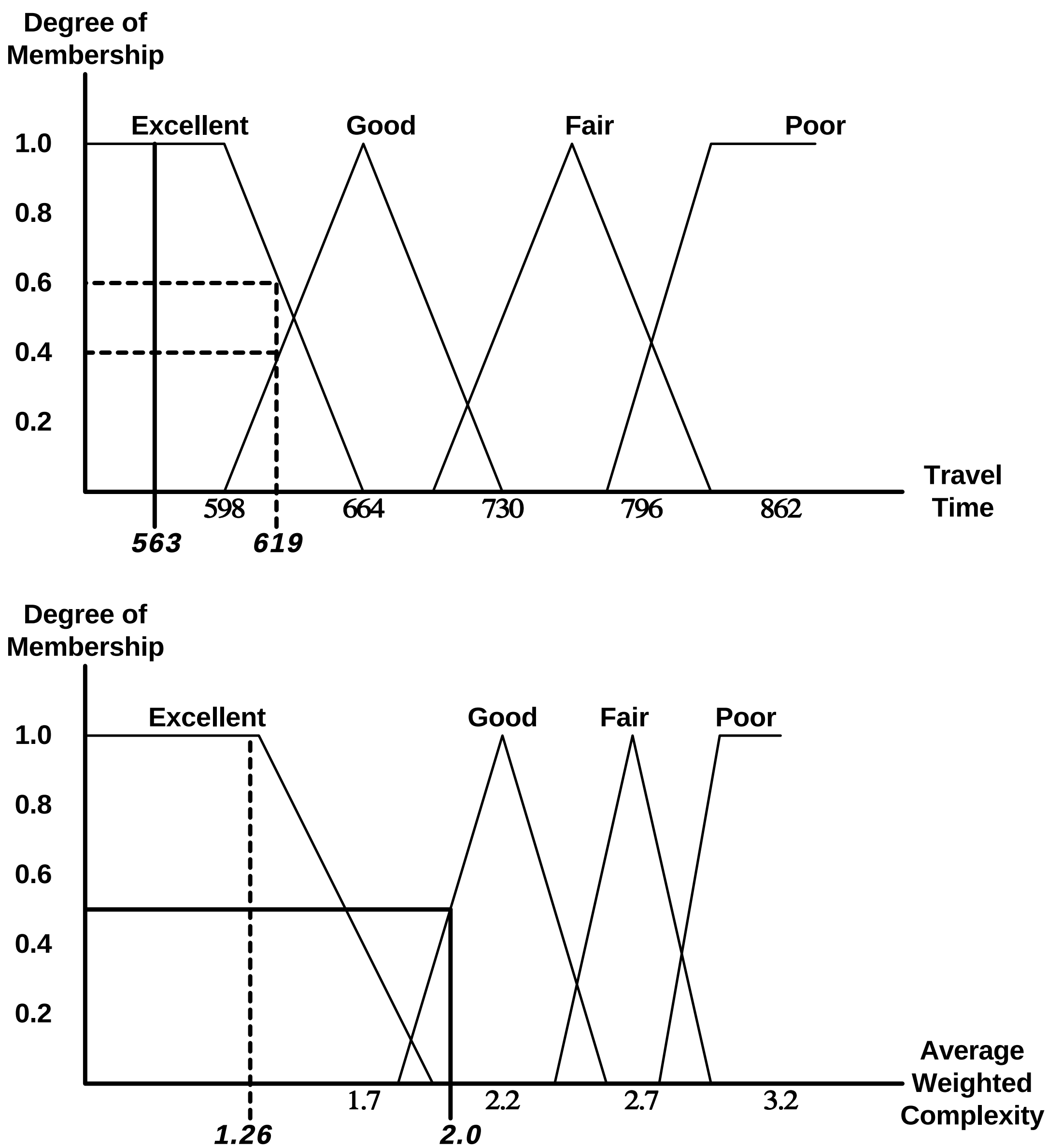

Figure 9: Assessing Current Conditions

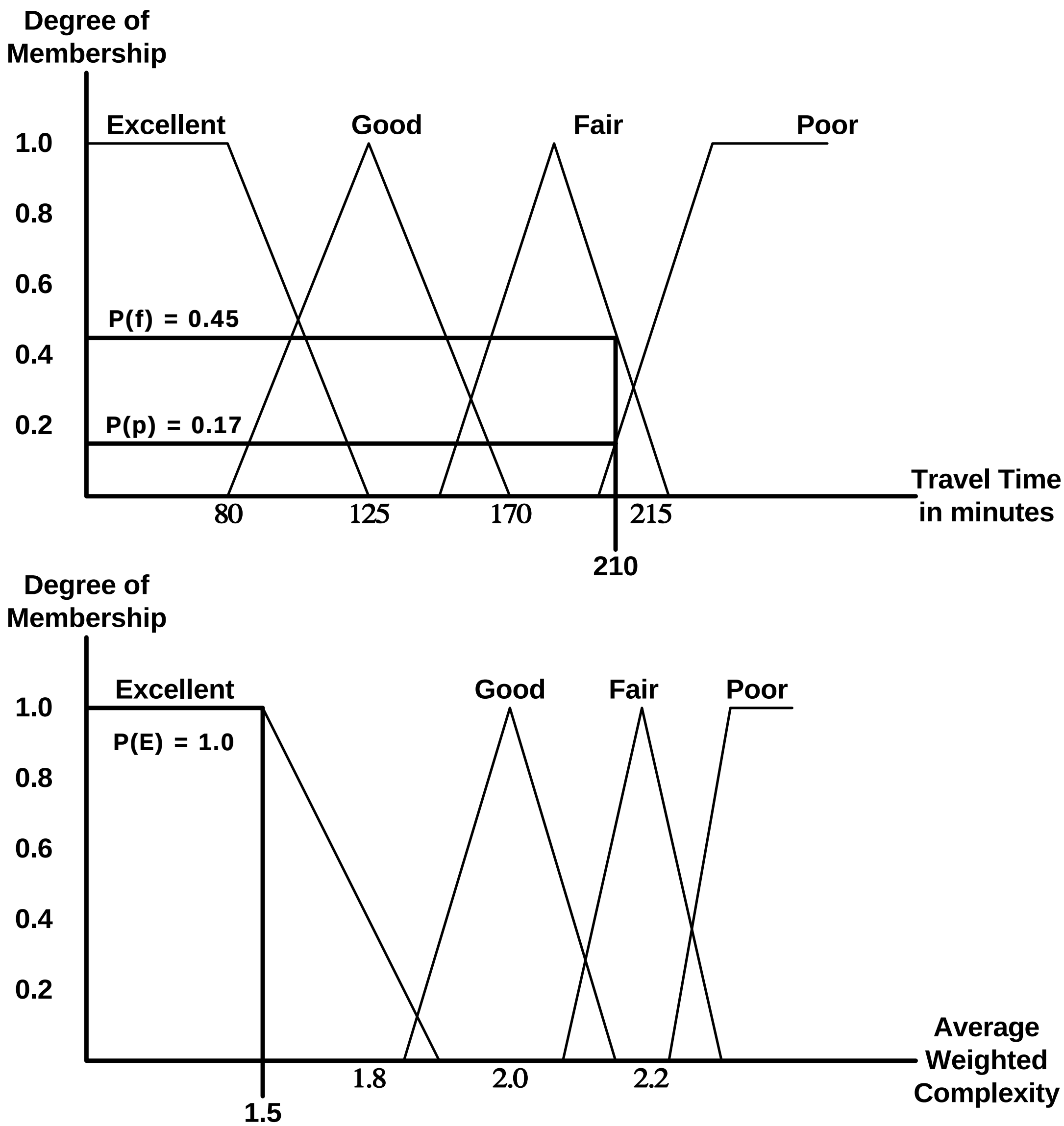

Figure 10: Finding the Centroid

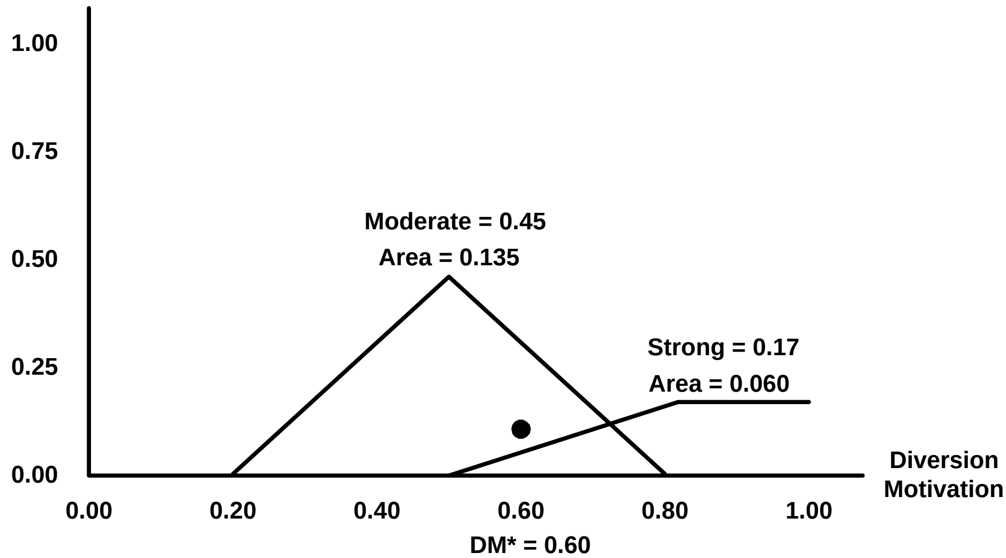

Figure 11: Fuzzy Rule Base for Route Utility

Complexity

Travel Time		***E***	***G***	***F***	***P***
	E	E	E	F	F
	G	G	G	F	F
	F	G	F	F	P
	P	F	F	P	P

E = Excellent; G = Good; F = Fair; P = Poor

Figure 12. Fuzzy Map for Route Utility

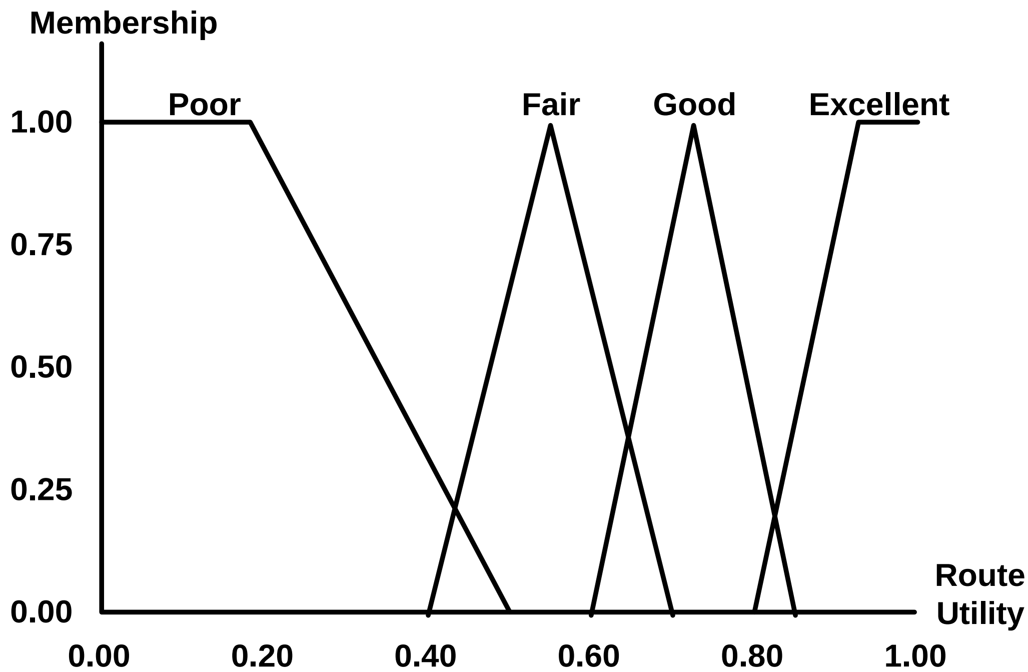

Figure 13. Rule Firings for Updated Current Path

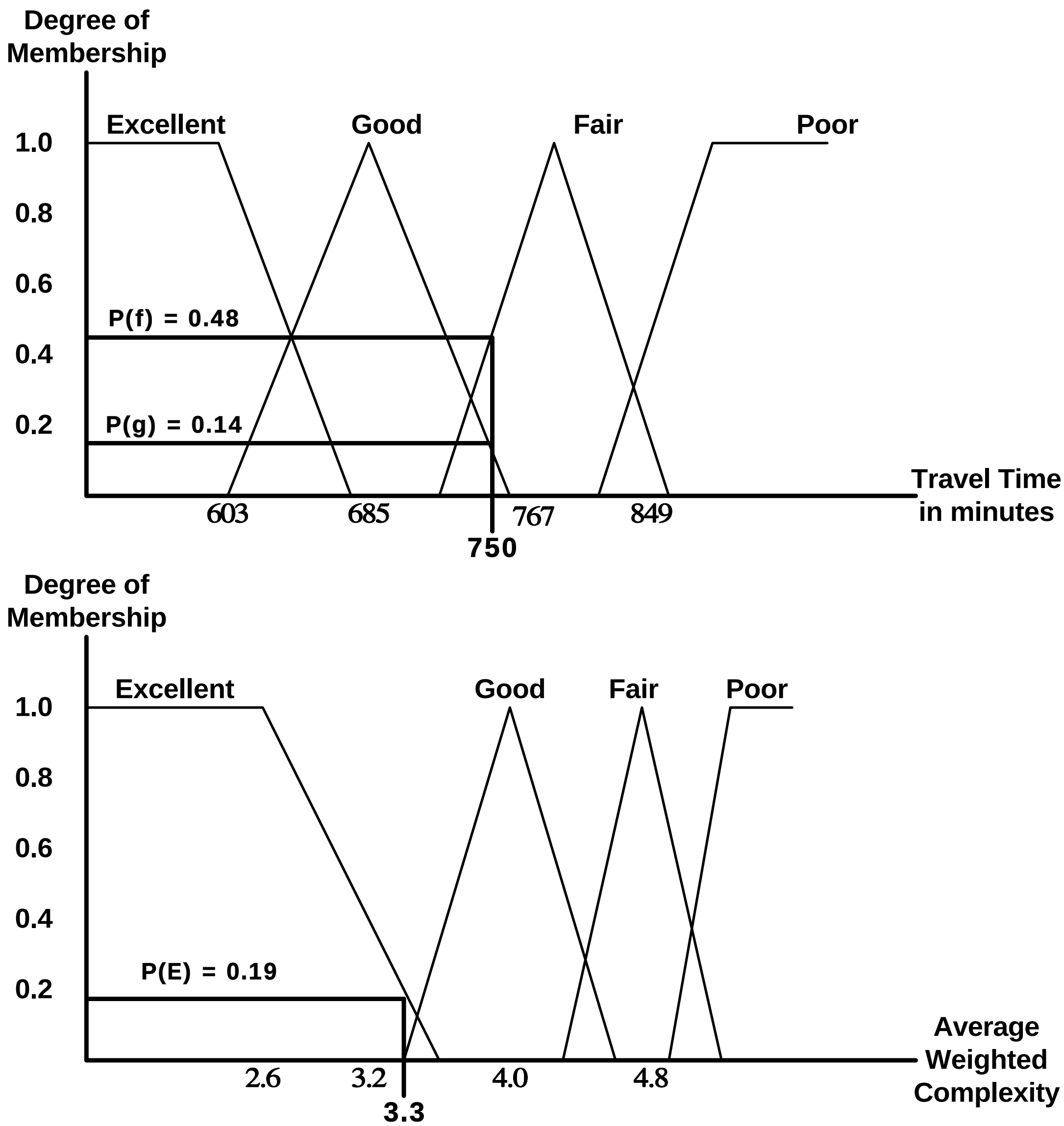

Figure 14. Rule Firings for Best Alternate Path