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A GENERALIZED APPROACH FOR ANALYZING TRANSPORTATION
USER PERCEPTION USING FUZZY SETS

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by
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ABSTRACT

A new approach for analyzing transportation user perception was developed using the concept of fuzzy sets. Due to the capability of fuzzy techniques to analyze subjective and uncertain matters, fuzzy set theory is an extremely useful tool for analyzing transportation user perception. To amplify the strength of the fuzzy approach for analyzing transportation user perception, several critical issues related to applying fuzzy techniques were reviewed, and existing fuzzy methods were adapted for use in the analysis of transportation problems. These new methods included procedures to determine fuzzy membership functions and to generate fuzzy rules.

This dissertation details the procedures followed to accomplish these tasks. First of all, appropriate types of fuzzy techniques, a fuzzy aggregation method and fuzzy inference system, identified from information about the various fuzzy set theories were selected based on a review of the related literature, studies related to transportation user perception, and previous fuzzy applications. Based on the selected fuzzy techniques, generalized fuzzy approaches for analyzing transportation user perception were developed. To develop these fuzzy approaches for transportation analysis, several details related to how each of the fuzzy approaches is applied were investigated. First, the relevant methods used to construct fuzzy membership functions for analyzing transportation user perception were identified. The use of these methods was illustrated by a series of real world applications as well. Second, the application of the fuzzy inference system, which is the most commonly used technique in fuzzy application studies, was explained. The appropriate ways to determine the structure of the fuzzy inference system and to generate the fuzzy rules were developed based on an understanding of the problems associated with analyzing transportation user perception. Third, a comparison was conducted between the perception of users from the general public and transportation experts. To investigate the applicability of using the opinions of groups of experts regarding the service quality of transportation systems as the surrogate of the opinion of groups of transportation users, statistical comparisons between the two were conducted.
To improve the developed fuzzy approaches and increase their applicability, two different transportation case studies using each of the two developed fuzzy approaches were conducted. The service quality of variable message signs (VMS) based on driver perception was evaluated using the fuzzy aggregation method. Existing survey results regarding the service quality of VMS were re-analyzed, and the overall satisfaction of the service of the VMS were aggregated. Experts’ opinions of crash factors associated with design and operational aspects of medians were incorporated using a hierarchical fuzzy inference system to evaluate median safety. Through the developed system, the degrees of median safety for real roadway segments were evaluated. Then, they were compared with observed median crash data.

Finally, two preliminary methods of validating fuzzy results were used, direct validation and indirect validation. An experimental study evaluating the service quality of signalized intersections was conducted to apply the direct validation. Using the observed crossover median crashes (CMC), the indirect validation method was applied. Based on these two preliminary validations, the developed fuzzy approach was found to be a suitable method for analyzing what drivers generally perceive from transportation systems when the unique characteristics of humans as transportation users is considered.

In conclusion, since transportation user perception is affected by many factors and the magnitude of the effect of each factor on transportation user perception is different between factors and between users, analyses considering those differences can produce better results in solving many types of transportation problems. For analysis of transportation user perception, the developed fuzzy approach can appropriately analyze user perception and produce more accurate and conceptually realistic results.

The basic concepts and specific procedures of the fuzzy approach developed herein can help to analyze appropriately transportation user perception. More accurate and realistic analysis of transportation user perception is enormously important for providing better transportation service to the public. The developed fuzzy approach enables designers and system operators to understand transportation user perception more thoughtfully, which can lead to a transportation system that is more conducive to providing service that leads to greater user satisfaction.
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CHAPTER 1
INTRODUCTION

User perception is a process that begins with the human sensory organs and ends in the brain. In certain aspects of transportation engineering, user perception is how users (i.e., drivers, passengers, bicyclists, or pedestrians) sense and understand roadway environments, passenger terminals, or information systems. As part of this process, they make judgments about levels of service, detect and recognize hazards, acquire and interpret information, and often make decisions in response to these inputs. As users constitute one of the three components of a transportation system; and in many respects the most important component, user perception is a critical element within the concept of transportation services. Transportation exists to provide high quality service to various user groups. The concept of user perception already has been used in many areas of transportation engineering, for instance, in the evaluation of ‘Level of Service’ or the analysis of users’ satisfaction through survey results. However, many of these measures of user satisfaction are not sufficient for explaining how “much” the users are satisfied or how much inconvenience they have experienced. Also, most of the current measures of effectiveness (MOEs) for transportation facilities have been created exclusively for evaluating the transportation system without focusing on the user. They have been not designed for explaining the needs, wants, and desires of the transportation system user (Pietrucha, 2001).

The conventional methods for evaluating user perception have limitations because the perception process of humans cannot be analyzed and assessed through a binary approach or in a simple quantitative way; conventional methods for evaluating user perception cannot fully explain it. The human thought process is subjective and complicated, and human perception cannot be represented by binary information. Human perception usually uses a linguistic approach rather than a numerical approach. For example, humans think and represent their thoughts of a flower as “That flower is very
beautiful,” not as “That flower is beautiful at level 5.” Also, humans are unable to acquire and process adequate amounts of information about environments related to specific facilities to formulate a “precise” response. This is one of reasons why human perception is subjective and not identical.

In the proposed study, the use of a fuzzy technique is applied as an alternative method for overcoming these limitations. A fuzzy approach is a method that can analyze any uncertain or ambiguous matters. The fuzzy approach is a very useful method for analyzing the uncertain and ambiguous terms that characterize human perception. Humans may evaluate the quality of a certain facility using their subjective satisfaction and represent it using their own linguistic terms, such as ‘good’ or ‘very good.’ It is not easy to distinguish the difference between ‘very good’ and just ‘good’ with conventional methods; however, a fuzzy approach may provide the means for formalizing the difference between these terms. Since the fuzzy approach can be used for describing approximate quantitative values, such as ‘about five,’ ‘below 100,’ and the like, fuzzy methods are likely to be an appropriate way to represent and analyze human perception.

The primary strength of a fuzzy approach is that it is applicable to human knowledge and the deductive process. Humans can manage complicated tasks under significant ambiguousness. This ambiguous information is represented through human linguistic terms and is used to deduct or make a decision. The clue or condition for human solution is a linguistic term, and the solution or decision is also a linguistic term.

There are many studies in areas other than transportation engineering that use a fuzzy approach to assess user perception. For example, fuzzy approaches can be used in the evaluation of business service quality (e.g., airline service counters, restaurants, bank waiting lines) or in studies of operator workload in industrial engineering settings. These methodologies may be transferable to the transportation field, especially for analyzing user perception of transportation facilities.

In this study, a generalized fuzzy approach for assessing user perceptions as they relate to transportation system elements will be formulated and case studies involving specific applications will be developed.
1.1 Research Objectives

The objectives of this research are to develop a new methodology for analyzing transportation user perception and to incorporate the developed methodology using particular transportation engineering problems. Specifically, the purposes of this proposed study are as follows:

- To review the literature on studies related to the evaluation of transportation user perception and to find the characteristics of transportation user perception as well as the limitations of the current methods used for analyzing it
- To review a fuzzy set theory, including the various fuzzy techniques and the applications of the concept of fuzzy sets into various areas including, but not limited to, the following: transportation engineering, the decision making process, and the evaluation of service quality in non-transportation areas
- To determine which of the fuzzy methods can be applied for analyzing transportation user perception based on the review of transportation user perception and fuzzy set theory
- To formulate a general methodology for employing fuzzy sets to analyze user perception in transportation engineering, including appropriate types of fuzzy approaches, ways to apply the fuzzy inference system
- To apply the general methodology to appropriate topics in transportation engineering as application case studies and to understand the limitations of the developed methodology
- To review and revise the proposed method using the experience obtained through the application case studies
- To validate the results of the proposed methodologies

To achieve these research objectives, two fuzzy approaches for the analysis of transportation user perception are developed. To apply these proposed fuzzy approaches, two different problems complete with existing data sets, which had been analyzed previously using conventional methods, were re-analyzed.
The main focus of this research is to develop a new methodology to more appropriately analyze subjective transportation user perceptions and to apply the proposed methodology using some real problems in transportation engineering.

1.2 Scope of Research

Based on the research objectives, the scope of this research is outlined below:

- A fuzzy approach for analyzing transportation user perception is developed based on the investigations of transportation user perception, fuzzy set theory and its application. Also, application of the developed fuzzy approach is detailed including construction of fuzzy membership functions and application of a fuzzy inference system.

- The developed fuzzy approaches are applied to transportation problems related to transportation user perception. Through this application, limitations to and problems associated with the developed fuzzy approaches and their details are found. These findings are used to make further improvements to the fuzzy approaches to analyze transportation user perception. The first application is an evaluation of the service quality of variable message signs using the fuzzy aggregation method. The second application is the evaluation of median safety based on expert opinion using a hierarchical fuzzy inference system.

- Validation methods for the fuzzy approaches and their results are developed and applied to the two different problems related to transportation user perception. The two transportation problems are the evaluation of service quality of signalized intersections and the evaluation of median safety on Interstate highways and expressways, which is somewhat different from the safety problem described above. These validations are conducted to allow a comparison to more conventional, non-fuzzy methods used to address these problems. Due to the extreme difficulty of validating user perception, the
validation conducted herein deviates somewhat from more conventional approaches.

1.3 Organization of Thesis

The remainder of the thesis will be organized in the following manner. The next chapter is a review of the relevant literature related to the evaluation of transportation user perception and studies applying fuzzy sets in three different areas. These three different areas include the following: transportation engineering, decision making processes, and evaluation of service quality in non-transportation areas. This chapter also details fuzzy set theory including the basic concept of fuzzy sets, fuzzy membership functions, and fuzzy inference systems.

In chapter 3, the methodology of the study, including a short description of application studies, is discussed. The explanation of the study methodology consists of three parts. The first part is concerned with the development of the general methodology for analyzing transportation user perception using fuzzy sets. In the second part, two application studies dealing with the evaluation of VMS service quality and the evaluation of median safety are described. In the last part of this chapter, procedures to validate the proposed methodology and fuzzy results are introduced.

Chapter 4 describes the generalized fuzzy approach for analyzing transportation user perception that is developed herein. This chapter explains primarily how to apply fuzzy set theory to evaluate transportation user perception. Throughout this chapter, the elements of the generalized fuzzy approach, which has been developed as the primary objective of this study, are described. These include the construction of fuzzy membership functions, determination of a structure of the fuzzy inference system, and fuzzy rule generation. Each element of the application of fuzzy set theory was developed based on two different types of fuzzy set approaches: fuzzy aggregation methods and fuzzy inference systems. Additionally, the results of a comparison of experts’ opinions with public opinions regarding the service quality of variable message signs (VMS) are presented.
Chapters 5 and 6 provide case studies of the application of the methodology described in chapter 4. In chapter 5, the first type of proposed fuzzy approach, the fuzzy aggregation method, was applied to evaluate the service quality of VMS. The existing data from a survey regarding VMS service quality, which consisted of ranking results using five linguistic ordered scales based on six criteria, were re-analyzed using the concept of the fuzzy weighted average and extended fuzzy operation algebras.

Chapter 6 describes the application of a hierarchical fuzzy inference system using two hierarchical levels, a lower level fuzzy inference system evaluating overall geometric conditions and an upper level evaluating the degree of median safety. The overall geometric condition was evaluated using five geometric variables, including median width, horizontal curvature, operating speed, median cross-slope, and shoulder width. ADT was used to describe the traffic flow condition. Using the geometric condition and the traffic flow condition, the overall degree of median safety was evaluated. This safety degree was represented by the final fuzzy outputs or a fuzzy median safety index. This index was compared with observed median crash data.

In chapter 7, an argument is made for the use of the proposed fuzzy approach as a more appropriate method to analyze transportation user perception. In this chapter, two methods of validating fuzzy results (i.e. direct validation and indirect validation) are proposed. Application of these two validation methods was conducted using transportation user perceptions regarding the service quality of signalized intersections and median safety.

Chapter 8 contains a summary of the research, the recommendations derived from the findings, the contribution of this work to transportation studies, and the need for further research to improve the method to analyze transportation user perception.
CHAPTER 2

LITERATURE REVIEW

A literature review was conducted covering three main topics: studies related to the evaluation of transportation user perception, introduction of fuzzy set theory, and studies applying fuzzy sets in various areas. Recently, several studies related to the evaluation of transportation user perception for various matters have been conducted. Most of the studies are about service quality of transportation systems based on user perception. There are a relatively small number of studies investigating the use of fuzzy techniques in the evaluation of transportation user perception. These studies are primarily focused on the service quality of transportation facilities, not other qualitative measures. As mentioned in the introduction, fuzzy set theory has been applied in many fields outside of transportation engineering including the evaluation of business service quality or studies of operator workload. Some of these fuzzy sets application studies were also reviewed.

2.1 Studies Related to Evaluation of Transportation User Perception

In the transportation engineering area, there are many kinds of MOEs for evaluating the transportation system. However, many of the current MOEs have been designed to simplify the evaluation of the transportation system by the manager, engineer, or researcher, and not for explaining the needs, wants, and desires of the transportation system user. Indeed, there is an increasing need to understand and use the information about travelers’ perception of service quality on transportation facilities as well as other qualitative problems such as safety, comfort, and ride quality. However relative few studies were conducted previously in transportation engineering wherein user perception was a central concern, even as the need for such information has increased. Also, there are some concerns about the need to improve the current level of service methodologies corresponding to transportation users’ perception.
Pietrucha (2001) argued that user perception should be incorporated into conventional engineering measures of effectiveness (MOE). He indicated that many of the current MOEs for the transportation system should be revised so that user perception of the transportation system can be considered. He also provided some recommendations about how user input might be incorporated into some MOEs.

Flannery and her colleagues (2004) reviewed different research approaches that could be used to evaluate drivers’ perception of service quality. The research approaches covered by the authors use uniquely different data collection methods: a survey with a focus group, video-based experiments, and an in-vehicle field method with a focus group. They explain that these three methods are the principal means of conducting user perception studies. They indicated that for many of the studies they looked at, these different methods produced similar results. They also mentioned that drivers commonly consider many factors in their evaluations of the service quality of transportation facilities. Further, drivers do not seem to consider the quality of their travel experience as being divided by segment or road type. This is different from the current means of segmenting roads for evaluation.

A study investigated the factors that impact traveler perceived quality of service on rural freeways using in-field surveys of motorist traveling on rural freeways (Washburn et al. 2004). They mentioned the ability to collect a relatively large sample size as the main advantage of the survey approach. To find how the factors affect the quality of the trip on a rural freeway, they asked drivers to rate several different road quality factors on a scale of 1 to 7 (1: not at all important and 7: extremely important). The subjects were also asked to rank the three most important quality indicators from the list of factors presented in the survey. From these data, they calculated a simple mean rank for each of the factors and the percentage of response for each factor from the “three most important factor” question. Drives identified six important factors, such as ability to consistently maintain drivers’ desired travel speed, ability to travel at a speed no less than the posted speed limit, ability to change lane and pass other vehicle easily, smooth and quiet road surface condition, other drivers’ etiquette/courtesy, and infrequent construction zones.
Pecheux and her colleagues (2004) used an in-vehicle field approach as well as a post-drive survey to determine the factors that affect automobile drivers’ perceptions of service quality on urban streets. Through these two experiments, they collected two kinds of driver perception. The first considers the relationship between the characteristics of the driving conditions and the drivers’ immediate reactions and evaluations through an in-vehicle field approach. The second indicates the relative importance of different features of urban streets through the post-drive survey. During the in-vehicle field experiments, participants spoke about their driving experience and the factors that influenced their perception of service quality. To determine the significant factors, they asked subjects to select five important factors and rank them. As a result, they provided the “scores based on Top 5 selected” produced by a sum of the ranking points. Through this simple calculation, visibility of signs and signals was selected as the most important factor for service quality on urban streets.

There are three experimental methods that have been commonly used for investigating transportation user perceptions: surveys or interviews, video-based experiments, and in-vehicle field methods (Flannery et al. 2004, Washburn et al. 2004, Pecheux et al. 2004). Each method has strengths as well as weaknesses. Selection of the appropriate method is a dominant theme in many research papers. For example, if there is a need to investigate which specific roadway features influence drivers’ perception of service quality, an in-vehicle field method may be the best method. If there is a need to investigate service quality perceived by a wider driving population, a survey method may be best. Table 2-1 shows the strength and weakness of each method as indicated in previous studies. However, a limitation that is common to all three methods is the difficulty of analyzing qualitative data commonly represented by linguistic terms. As mentioned previously, the proposed method, applied fuzzy sets, can mitigate the problem. To illustrate the proposed fuzzy set method, the results of a previous study using one of those experimental methods were reanalyzed.
Table 2-1: Various Methods for Evaluating Driver Perception of Transportation Service Quality.

<table>
<thead>
<tr>
<th>Methods</th>
<th>Strength</th>
<th>Weakness</th>
</tr>
</thead>
</table>
| Survey or interview         | · Representative of the wider driving population or overall driving environments  
                               | · Possible to collect a relatively large sample size  
                               | · Cost effective method regarding sample size.                                                | · Removed from the immediate driving environments of the roadway  
                               |                                                                                               | · Difficult to collect drivers’ perceptions regarding specific roadway conditions  
                               |                                                                                               | · Difficult to investigate the insight into drivers’ thought, perceptions, and evaluations of roadway conditions |
|                             |                                                                                                                                 |                                                                                               |
| Video-based simulation      | · Possible to present repeatedly to participants  
                               | · Possible to conduct the experiments with controlled condition to investigate the effect of given conditions | · Removed from the immediate driving environments of the roadway  
                               |                                                                                               | · Difficult to collect large size of data  
                               |                                                                                               | · Not cost effective method regarding sample size. |
|                             |                                                                                                                                 |                                                                                               |
| In-vehicle field method     | · Possible to investigate the insight into drivers’ thought, perceptions, and evaluations of roadway conditions  
                               | · Possible to obtain the issues that matter to drivers in a actual driving experience  
                               | · No removed from immediate driving environments of the roadway | · Difficult to collect large size of data  
                               |                                                                                               | · Not cost effective method regarding sample size.  
                               |                                                                                               | · Difficult to collect the perception from various driver characteristics  
                               |                                                                                               | · Difficult to collect data with real driving situation(e.g. time pressure) |
2.2 Fuzzy Set Theory

2.2.1 Introduction of Fuzzy Set Theory

The concept of fuzzy sets was first introduced by L. A. Zadeh in 1965. Since this introduction, it has been used in many areas related to human perception, such as the evaluation of service quality and the analysis of workload and risk in the workplace. Fuzzy sets, where a more flexible sense of membership is possible, are classes with unsharp and vague boundaries. Fuzzy set theory is a branch of a set theory that is useful for the representation of imprecise knowledge of the type that is prevalent in human concept formation and reasoning because fuzzy theory can represent a type of uncertainty due to vagueness or fuzziness (Yen and Langari 1998, Tsoukalas and Uhrig 1996, and Yager 1986). The concept of fuzzy sets has been developed for various types of analysis methods, such as fuzzy numbers, fuzzy relations, and fuzzy inference systems. Recently, these fuzzy sets have been combined with statistical methods and other intelligent methods, for example, neural networks and genetic algorithms. The basic fuzzy set method consists of three components; fuzzification, fuzzy operation, and defuzzification. In this chapter, fuzzy sets are described in greater detail including the comparison of fuzzy sets with classical sets, fuzzy membership function, and fuzzy inference system. However since the determination of fuzzy membership functions is the most important task, and it is one of main issues in the proposed study, it will be the focus of the narrative.

2.2.2 Classic Set and Fuzzy Set

A classic set can be defined as a collection of objects in a given domain. An object should either belong to the set or not belong to the set. Therefore, there is a sharp boundary between members of the set and those not in the set. Yen and Langari (1998)
describe the limitations of the classical set theory in solving real problems. A set in classical set theory always has a sharp boundary because membership in a set is a black-and-white concept (an object either completely belongs to the set or does not belong to the set at all). In real problems, two types of sets exist. Some sets do have sharp boundaries (e.g. the set of married people), others do not have sharp boundaries (e.g. the set of happily married couples, the set of good graduate schools). Classic sets cannot be used to analyze those sets with un-sharp boundaries.

A fuzzy set is as a set with “un-sharp” and vague boundaries. It generalizes the notion of membership from a black-and-white binary categorization in classical set theory into one that allows partial membership. Fuzzy set theory can overcome the limitations of the classical set theory by allowing membership in a set to be a matter of degree. The degree of membership in a fuzzy set is represented by a number between 0 and 1; 0 means entirely not in the set, 1 means completely in the set. Figure 2-1 shows the difference between a classical set and a fuzzy set.

![Figure 2-1: The Classical Set and the Fuzzy Set.](image)

**2.2.3 Probability Theory and Fuzzy Set Theory**

When considered as research tools, probability and fuzzy sets have some similarities as well as some differences. Yen and Langari (1998) describes the two concepts as follows:
Fuzzy logic and probability theory are two different tools, like screw drivers and hammers. They were designed for different tasks. One could conceivably use a hammer to hammer a screw, yet it is much more effective to use a screw driver for the job.

Probability measures “likelihood of occurrence.” This probability is related to the following question, “How often or frequently does it happen?” While a fuzzy set measure “the degree of certainty” and is related to following question, “How sure are you that it happens?” Zadeh mentioned the limitations of applying probability theory to matters related to human cognition in a 2002 study. He stated that this limitation is due to the lack of probability theory to operate on human perception-based information, which is commonly described through a natural language.

However, probability theory and fuzzy logic are complementary rather than antagonistic or competitive (Zadeh, 2002). In other words, as they deal with different matters they can work “together” and complement each other. Fuzzy sets operate on “perception-based information” which is expressed by linguistic terms. Also fuzzy sets are a better tool to analyze problems that have an un-sharp or gray area of judgment. Probability lacks a capability to operate on perception-based information, which is a product of human cognition. The development of fuzzy set models was motivated by a desire to have a method for dealing with reasoning tasks, while Bayesian approaches are oriented toward rational decision-making. These two approaches are based on two different understandings of what certainty is (Dubois and Prade 2000).

### 2.2.4 Membership Function

Membership function is the most important element of the fuzzy approach, and it allows the fuzzy approach to evaluate uncertain and ambiguous matters. The role of the membership function is to represent an individual and subjective human perception as a member of a fuzzy set. A fuzzy set has several membership functions, $u_F$, defined as
functions from a well defined universe, \( x \), into a unit interval, 0 through 1 as shown in the following equation (Eq. 2.1):

\[
u_F : X \rightarrow [0,1] \tag{Eq. 2.1}
\]

This membership function can represent the degree of the subjective notions of a vague class with an infinite set of values between 0 and 1. The task of determining the membership function is the most critical step in a fuzzy analysis procedure. Also, one of the most difficult tasks for applying fuzzy sets is to correctly measure the membership function. The measurement of the membership function varies according to the topic being analyzed.

### 2.2.4.1 Types of Fuzzy Membership Function

There are numerous types of fuzzy membership functions including triangles, trapezoids, bell-shape curves, S-shape curves, \( \Pi \)-shape curve, Gaussian, and sigmoid function. Of all of these functions, the most commonly used in practice are triangles, trapezoids, bell curves, Gaussian, and sigmoid functions. Due to those various types of membership functions, the selection of the type of membership function is an important and critical step for accurate fuzzy set application. The type of membership function selected is a function of the analyst’s judgment based on a thorough review of the data. The following guidelines are general rules to select the type of membership function.

- The simplest types are triangular and trapezoidal functions. Due to their simple formulas and computational efficiency, both membership functions have been used popularly and extensively in fuzzy sets applications.
- Between the triangular and trapezoidal functions, the trapezoidal function is better than the triangular function if there is more variance in the data sets.
Some curved membership functions such as bell curves, Gaussian, and sigmoid function, are better if there are large numbers of data. They can produce more accurate results.

Table 2-2 describes the formulas and parameters of each membership function and shows examples of each. As can be seen in table 2, the triangular and bell-shape curve functions are specified by three parameters, and the Gaussian and sigmoid functions are determined by two parameters. Trapezoidal function consists of four parameters. These parameters control the exact shape of the membership function and the function values. The desired membership function is obtained by an appropriate selection of these parameters.
Table 2-2: The Various Types of Fuzzy Membership Functions.

<table>
<thead>
<tr>
<th>Type</th>
<th>Function equation</th>
<th>Example</th>
</tr>
</thead>
</table>
| Triangle   | \( f(x; a, b, c) = \begin{cases} 
  0 & x \leq a \\
  \frac{x-a}{b-a} & a \leq x \leq b \\
  \frac{c-x}{c-b} & b \leq x \leq c \\
  0 & c \leq x 
\end{cases} \) | ![Triangle Function](triangle.png) |
| Trapezoid  | \( f(x; a, b, c, d) = \begin{cases} 
  0 & x \leq a \\
  \frac{x-a}{b-a} & a \leq x \leq b \\
  \frac{1}{b-a} & b \leq x \leq c \\
  \frac{c-x}{c-b} & c \leq x \leq d \\
  0 & d \leq x 
\end{cases} \) | ![Trapezoid Function](trapezoid.png) |
| Bell Curve | \( f(x; a, b, c) = \frac{1}{1 + \left( \frac{x-c}{b-a} \right)^{2b}} \) | ![Bell Function](bell.png) |
| Gaussian   | \( f(x; m, \delta) = \exp \left( -\frac{(x-m)^2}{\delta^2} \right) \) | ![Gaussian Function](gaussian.png) |
| Sigmoid    | \( f(x; a, c) = \frac{1}{1 + e^{-a(x-c)}} \) | ![Sigmoid Function](sigmoid.png) |
2.2.4.2 How to Interpret the Grade of Membership Function

The interpretation of degree of membership is another issue in the fuzzy set theory. It can be represented with following question.

“What does it mean to say \( u_F(x) = A_i ? \)”

Dubois and Prade (2000) introduced five interpretation methods that are commonly used as follows:

[“John \((x)\) is tall \((T)\)” – “What does it mean to say \( u_F(x) = 0.7 ? \)”]

Table 2-3 explains various interpretation methods for grade of membership function, and Figure 2-2 shows which type of experimental method is appropriate for each interpretation of fuzzy membership function.

<table>
<thead>
<tr>
<th>Method</th>
<th>Interpretation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Likelihood</td>
<td>“70% of a given population declared that John is tall”</td>
</tr>
<tr>
<td>Random set</td>
<td>“70% of a given population described “tall” as an interval containing John’s height”</td>
</tr>
<tr>
<td>Similarity</td>
<td>“John’s height is away from the prototypical object which is truly “tall” to the degree 0.3”</td>
</tr>
<tr>
<td>Utility method</td>
<td>“0.7 is the utility of asserting that John is tall”</td>
</tr>
<tr>
<td>Measurement method</td>
<td>“When compared to others, John is taller than some and this fact can be encoded as 0.7 on some scale”</td>
</tr>
</tbody>
</table>
2.2.4.3 Fuzzy Inference System

The primary strength of a fuzzy approach is that it is applicable to human knowledge and the deductive process. Fuzzy inference is the deductive process of formulating the mapping from a given input to an output using fuzzy logic. Humans can manage complicated tasks under significant ambiguity using reasoning or an inference process. This ambiguous information is represented through human linguistic terms and is used to deduce or make a decision. This deductive reasoning method with linguistic terms using fuzzy sets is a fuzzy inference system. It is also called the fuzzy logic or if/then rule, and it models the human decision-making process. A fuzzy rule has two components: an if-part (also referred to as the antecedent) and a then-part (also referred to as the consequent):

$$IF <\text{antecedent}>, THEN <\text{consequent}>$$
The antecedent describes a condition, and the consequent describes a conclusion that can be drawn when the condition holds. For example, if service is excellent or food is delicious, then tip would be generous in Figure 2-3. Usually, this inference follows 5 steps:

1. **To fuzzify inputs**
   
   This first step is to take the inputs and determine the degree to which they belong to each of the appropriate fuzzy sets through membership functions.

---

**Figure 2-3: An Example of Fuzzy Inference System**

ii. To apply fuzzy operator

If the antecedent of a given rule has more than one part, the fuzzy operator is applied to obtain one number that represents the result of the antecedent for that rule; and, or, complement, product, multiplying, and power of fuzzy set.

iii. To apply implication method

Before applying the implication method, the rule’s weight between 0 and 1 should be applied.

iv. To aggregate all output

Since decisions are based on the testing of all rules in a fuzzy inference system, the rules must be combined in some manner to make a decision.

\[ \text{e.g.} \] If service is poor or food is rancid, then tip is cheap.

\[ \text{If service is excellent or food is delicious, then tip is generous} \]

v. To defuzzify

The result is described with a fuzzy value and must then be translated into a single natural number (crisp set)

Based on the type of the consequent, two main types of fuzzy inference systems are distinguished: Mamdani fuzzy inference and Takagi-Sugeno fuzzy inference. The Mamdani fuzzy inference system uses a linguistic value and a fuzzy value for both the antecedent and the consequent. In the Takagi-Sugeno fuzzy inference system, the antecedent is a linguistic value, but the consequent is a crisp function, which is a linear equation with input variables (e.g. \( z = ax + by + c \), where \( a, b, c \) are numerical constants).

A fuzzy inference system includes four main procedures: fuzzification, generation of the fuzzy membership function and fuzzy rules, fuzzy inference, and defuzzification as can be seen in Figure 2-4.
2.3 Fuzzy Application Related to the Proposed Study

Since the introduction of fuzzy sets (Zadeh 1965), fuzzy approaches have been applied to many areas including civil engineering. It has been mainly used in control engineering, decision science, and management. The strength of fuzzy set theory is in its ability to establish numerical inputs from subjective and ambiguous information, to analyze or evaluate the information, and to produce numerical outputs from those procedures. Due to those strengths, it is especially useful for the representation of imprecise and subjective knowledge of the type that is prevalent in human concept formation and reasoning (Yager, 1986). Indeed, the fuzzy approach has already been used in many areas related to human perception, such as the evaluation of service quality, the analysis of workload and risk in the workplace, and decision making processes. In areas related to civil engineering, there are studies evaluating pavement condition and qualitative measurements including transportation service quality using the fuzzy approach. Three main topics, which apply fuzzy set theory, were reviewed including the applications of fuzzy sets in transportation engineering, decision making processes, and evaluation of
service quality. In this chapter, some fuzzy set applications related to the proposed study are introduced. A more detailed explanation of fuzzy sets is provided in the next chapter.

### 2.3.1 Transportation Engineering

Early on, fuzzy set theory was mainly applied in transportation engineering for traffic control (Robertson 1979, Favilla et al. 1993) and accident prediction. However, those applications are not related to this study as they used different approaches from those that would be used to evaluate user perception, which is the main topic of this study. Therefore, literature related to traffic control and accident prediction were excluded from review in this study.

In the late of 1970s, Blockley emphasized the analysis of system and human uncertainty in civil engineering and suggested the use of fuzzy set theory in civil engineering. Many civil engineering projects require a significantly high level of safety.

While engineers use their judgment and make decisions based on their scientific knowledge and experience, some of these processes include a certain amount of uncertain information, which can cause significant problems. He indicated that fuzzy sets can mitigate the problems related to the significant difficulty of calculating the uncertainty surrounding civil engineering projects. To illustrate the proposed fuzzy approach, he showed two numerical examples. Even though the method proposed by the author was related to structural analysis, and not transportation engineering, his suggestion of the role of fuzzy sets in civil engineering is an indication of the potential importance of applying fuzzy sets in transportation engineering, especially for the evaluation of user perception. This is because one of the three main components of the transportation system is human, and a human’s perception and decision making always includes variety and uncertainty.

Another researcher who indicated the importance of applying the fuzzy sets in transportation engineering was Spring (2000). He mentioned that fuzzy sets are able to represent vague and imprecise concepts in transportation engineering, such as the service quality of transportation facilities.
The evaluation of the service quality of transportation facilities is one of the most significant processes in transportation engineering. Currently, the level of service concept in the Highway Capacity Manual (HCM) has been the most widely used means for evaluating the service quality of various transportation facilities. However the HCM methods have been devised for the evaluation of the transportation system without focusing on the user. To overcome this problem, fuzzy sets have been applied in some studies. There are two studies that applied fuzzy sets to evaluate transportation service quality, typically to evaluate LOS.

Ndoh and Ashford applied fuzzy sets to evaluate airport terminal service quality in their 1995 study. They indicated that conventional methods to evaluate the transportation service quality are quantitative measures and are reasonably simple to measure but these measures are deficient in representing the qualitative nature of service quality for transportation facilities. These methods may not be able to incorporate directly users’ perceptions of LOS. To remedy this situation, they developed a methodology for establishing LOS measures based on users’ perception and then applied the method to evaluate airport terminal service quality. They established five criteria that represent airport service quality, such as processing activities, holding facilities, and amenities, and each criterion has several sub-criteria for evaluating service quality. The authors also provided an example that demonstrated how to evaluate these service qualities using their fuzzy approach. One drawback to the study was that they merely broached the possibility of using fuzzy sets to evaluate LOS for airport terminal and only provided a framework, not a specific method regarding the fuzzy set application.

Fang et al. (2003) tried to incorporate user perception in defining the LOS categories using a fuzzy C-means clustering technique. They stated that the fuzzy set is an instrument that makes use of human knowledge and the deductive processes. The authors also indicated that they used fuzzy clustering as the method for classifying user perception of service quality for two reasons. One is that fuzzy clustering can explain numerically the flexible and subjective LOS categories. Another is that this method can describe the subjective variation and vagueness in user perception. They used a fuzzy C-means clustering technique to classify the data set of the estimated delay and the LOS
rated by 100 subjects. Through their results, they suggested that the fuzzy cluster approach is an appropriate method to define categories that have uncertainties associated with them and can be estimated subjectively.

Recently there was an effort to apply fuzzy sets to measure traffic congestion. Hamad and Kikuchi (2002) proposed a method to measure the degree of traffic congestion on arterial roadways using a fuzzy inference system. They indicated that the problems with conventional methods of measuring traffic congestion are the derivation of measures that involve uncertainty. They stated the uncertainty was created by imprecision of the measurement, the traveler’s perception of acceptability, variation in sample data, and the analyst’s uncertainty about causal relations. These problems exist with most qualitative measures of human perception. Under these circumstances, they introduced a fuzzy inference system for measuring traffic congestion that aggregate the notions of travel speed and delay, which are main MOEs, into a single index. Figure 2-5 depicts their fuzzy inference system. They used two factors in the antecedent parts including “travel speed rate” and “very low speed rate.” Then 18 fuzzy rules were constructed to measure traffic congestion. As with most fuzzy application studies, they did not describe sufficiently how to determine membership functions and their appropriation. Also, they did not indicate how to construct the fuzzy rules. In other words, the two antecedent parts and a consequent part of the fuzzy rules might be connected instinctively by analyst’s knowledge and experience. However, these two problems are a key that control the accuracy of results. Further, these problems can be moderated by employing data regarding variables in the antecedent and consequent part as a supplementary method.
Juang and his colleagues (1993) recommended the application of fuzzy set theory in civil engineering, especially transportation engineering. They emphasized the need to elicit numerical data from subjective information in the analysis of many transportation...
This elicitation of numerical data from subjective information usually includes the uncertainty due to imprecise information and various factors influencing the information. They introduced three main procedures for general fuzzy set application. The first step was the representation of the fuzzy information. That subjective information is easy to represent using linguistic terms. Through this step, these linguistic terms were transformed into numerical data, which were defined by fuzzy membership functions. The second step was the processing of the fuzzy information through a fuzzy operation method. The last step was the interpretation of the fuzzy information. In this step, the output represented by the fuzzy sets was transformed again into appropriate linguistic terms. They suggested that the proposed method is suitable for analyzing subjective information and mentioned that this approach should be considered appropriate for solving many transportation engineering problems.

The area that fuzzy set theory has been applied to most frequently in problems related to transportation engineering is in the evaluation of pavement condition. This is due to the difficulty of quantitatively assessing pavement condition. Loizos (2001) applied fuzzy set theory to evaluate the subjective pavement roughness that drivers “feel” on the road. Pavement roughness has been used as a measure of ride quality, and it is represented through indices such as the International Roughness Index (IRI). IRI is actually an objective measure recorded by devices such as laser profilers. However, this index does not represent the subjective ride quality that an individual driver feels on the road. Loizos developed a fuzzy model that was based on a subjective appraisal of road quality gathered from panels of road users. In this study, five linguistic rating levels of road quality were mapped by fuzzy logic.

Shoukry et al. (1997) suggested a new way to evaluate pavement condition using fuzzy set applications. They detailed the shortcomings of traditional methods by explaining that there were possible inaccuracies in results due to errors in the pavement data collection and data recording procedure. Under these circumstances, they emphasized the need to develop a more efficient and general method that can evaluate accurately a large transportation network. In their study, fuzzy set theory was used to develop this more efficient and general method of evaluating the pavement condition. A
set of fuzzy membership functions was used to explain various parameters in the database. These functions considered the human perception regarding each parameter’s significance and described a typical relation between each parameter value and the degree of the characteristics of each parameter class. The authors stated as a conclusion that the fuzzy set model developed in this study could had the flexibly to evaluate the pavement condition given the characteristics of a single area and evaluate the network wide pavement condition as well. The model can also incorporate both the numerical and linguistic measurements that are included in database. Finally, they concluded that the proposed fuzzy distress index model was a suitable measure of the whole pavement condition so that it could be used for any pavement section.

2.3.2 Decision Making Processes

Another area in which fuzzy sets have been applied widely is decision making processes. The decision making processes are defined as a process of choosing the most appropriate alternative or decision from a set of alternatives to attain certain goals. This is because most decision making processes involve uncertainty, and one of the most critical aspects in selecting the appropriate decision is the handling of imprecise and vague information (Ribeiro, 1996). This information is commonly described by linguistic terms, for example ‘large’ profits, ‘fast’ processes, and ‘cheap’ costs. These circumstances occur similarly in transportation engineering. In transportation engineering, the decision making process is needed in various project stages. It is closely related to user perception of transportation service quality because to evaluate the service quality perceived by users is another version of decision making. The biggest difference between a typical decision making process and user perception of transportation service quality is who makes the decision. In a typical decision making process, experts or people who are very familiar with the area usually make the decision. In evaluating transportation service quality, people or the public, not experts, evaluate the service and decide their perceived level of service quality.
In decision making processes, several categorical criteria with differing levels of importance are used to evaluate alternatives. To evaluate the alternatives according to the stated criteria requires procedures that aggregate the result for each criterion across each subject. The information from those several categorical criteria should be aggregated. One of common aggregation method is use of the concept of the weighted average based on fuzzy set theory, which is called a fuzzy weight average. The fuzzy weighted average method was developed by Dong and Wong (1987). They developed the computation method using fuzzy weighted averages and implementation of the extension principle. This fuzzy weighted average is based on extended algebraic interval operations and the concept of an $\alpha$-cut representation of fuzzy number. This method has been commonly used in a multiple decision making processes. However, they did not mention the issue of eliciting of importance (weights), which is significant step in a fuzzy decision making method.

Many years ago, Saaty (1977) developed the hierarchical method to determine the weights of criteria using the principal eigenvector of a positive pair-wise comparison matrix. This eigenvector method was modified by applying the concept of a fuzzy set by Juang, et al. (1992). They developed the fuzzy eigenvector method estimating the weight of each criterion in their study. Juang and his colleagues indicated that the weight of each criterion, which represents the importance of each criterion, can be determined more precisely by the fuzzy eigenvector method. However, since the procedures of fuzzification and defuzzification were repeated in their study, the final results could be biased or lose the unique personal characteristics of the individual subjects. There are also several other studies related to fuzzy aggregation methods including the fuzzy average method.

Ribeiro (1996) reviewed and summarized the previous main theories and methods used for multiple attribute decision making in a fuzzy environment. He also proposed an elicitation method to determine the attributes’ importance. He indicated that a useful decision model must operate with incomplete and uncertain knowledge and information and that different views, attitudes, and beliefs must also be considered. Under these circumstances, he mentioned that probability and fuzzy sets are the appropriate method to
evaluate multiple attribute decision making. However, as Zadeh (1965) stated earlier, fuzzy set theory was the most proper method because impression multiple attribute problems could be incorporated using fuzzy sets to define attribute and the importance of attributes. Through his study, he suggested that the fuzzy decision making method be simplified by using a simpler assignment of importance schemes with the most efficient aggregation method.

### 2.3.3 Evaluation of Service Quality in Non-Transportation Engineering Fields

Fuzzy sets have largely been applied to evaluate business service quality not related to transportation, such as the quality of technical support service, an organization’s service to members, and other business services. Rao, et al. developed a method for the quantification of consumers’ perceptions of technical support service quality in their 1998 study. They indicated that consumers’ perceptions of service quality are very qualitative and subjective. For analyzing those qualitative and subjective perceptions, they mapped the subjective quality level assessments through a fuzzy linguistic analysis technique. In this study, the subjective levels of technical support service quality were converted into objective functions and evaluated by a fuzzy linguistic scaling approach using individual subject responses. In their experiment, participants responded two types of questions. The first type of question was about overall service quality and the second type of questions was about service questions based on seven criteria, including cost, expertise level, courtesy level, response time, ease of accessibility level, confidentiality level, and wait time. Figure 2-6 shows the set of questions used. Figure 2-7 shows the fuzzy membership function representing the degree of technical support service in each criterion.
<table>
<thead>
<tr>
<th>Response time:</th>
<th>Short</th>
<th>Medium</th>
<th>Long</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wait time to get response:</td>
<td>Short</td>
<td>Medium</td>
<td>Long</td>
</tr>
<tr>
<td>Courtesy of technical support personnel:</td>
<td>Low</td>
<td>Medium</td>
<td>High</td>
</tr>
<tr>
<td>Ease of accessing support:</td>
<td>Low</td>
<td>Medium</td>
<td>High</td>
</tr>
<tr>
<td>Confidentiality of Service:</td>
<td>Low</td>
<td>Medium</td>
<td>High</td>
</tr>
<tr>
<td>Cost</td>
<td>Low</td>
<td>Medium</td>
<td>High</td>
</tr>
<tr>
<td>Expertise of technical support personnel:</td>
<td>Low</td>
<td>Medium</td>
<td>High</td>
</tr>
<tr>
<td>How likely you are to use the service:</td>
<td>1 2 3 4 5 6 7 8 9</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Your perception of the quality of this service:</td>
<td>1 2 3 4 5 6 7 8 9</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 2-6: Questions in the Rao's Experiment

Figure 2-7: Fuzzy Membership Function Representing Technical Support Criteria
Chen (2001) proposed a fuzzy linguistic decision making method to evaluate service quality. He indicated that the fuzzy set approach is the most appropriate method to evaluate service quality because service quality problems utilize uncertain and imprecise data. In his study, the customers’ subjective opinions and the weight of factors were described by the fuzzy linguistic scales. He considered the importance of each criterion and computed the overall fuzzy ratings of all alternatives using fuzzy number operations. To evaluate the service quality of three service organization, he used five benefit criteria: reliability, responsiveness, altitude, support, and speed.

Lee and Chen (2002) developed a method of evaluating service quality using a process capability index with fuzzy numbers. This index considered both the average and the consistency of the data simultaneously. They indicated that the limitation of traditional approaches was that they did not consider the consistency of the customers’ perceptions, thus making comparison difficult. They applied fuzzy numbers of linguistic variables that represented the degree of the service quality to modify the process capability index. Then they applied it to evaluate the service quality perceived by customers. They mentioned that their proposed approach could evaluate the service quality by considering the average satisfaction of customers and dispersion of those customers’ feelings simultaneously. The strength of this fuzzy approach, as mentioned by the authors, was that customers can describe their feelings of satisfaction directly using linguistic terms, and analyst could evaluate the customers’ opinions quantitatively through transforming the linguistic terms into fuzzy numbers.

2.4 Summary

As reviewed in previous sections, the studies that evaluate transportation user perception are based on linguistic methods rather than numerical methods. Generally, three data collection methods have been used to analyze transportation user perceptions, including surveys or focus groups, video-based experiments, and in-vehicle field methods. However, once the data are collected, many researchers analyze their data using simple calculations to reduce user inputs derived from rankings or linguistic scales.
There are some limitations in analyzing user perception data using those conventional methods. To overcome these limitations, development of a new method to provide a more appropriate analysis of transportation user perception is needed. Indeed, the 2004 Transportation Research Board’s Committee on Highway Capacity and Quality of Service indicated the limitation of their method of assessing service quality. They stated that an appropriate method to analyze linguistic data representing human perception is needed.

Since Zadeh introduced the concept of the fuzzy sets, it has been applied in many areas and within various types of methods such as fuzzy reasoning, fuzzy numbers, fuzzy logic, fuzzy regression, and other fuzzy methods. The most important difference of a fuzzy set with a classic set is the property of “vague boundaries.” In fuzzy sets, elements have degrees of membership ranging from 0.0 to 1.0 in a set. This concept of fuzzy sets has been applied in many studies related to human perception, which having vagueness and fuzziness. Membership function is the most important element of the fuzzy approach, and it allows the fuzzy approach to evaluate uncertain and ambiguous matters.

Even though fuzzy sets have been applied in various areas, there was no general method to apply these methods for transportation user perceptions. Also, the determination of fuzzy membership function was not mentioned in the most studies applying the fuzzy sets. In those studies, membership functions were determined intuitively, or the membership functions of other similar studies were used without any concern of what the topic was. Another deficiency of the reviewed studies was data collection and data formation. There was a need to investigate these issues so that the use of fuzzy sets in transportation engineering can be made more convenient.
CHAPTER 3

METHODOLOGY

The primary objective of this study is to apply fuzzy theory, as described in the preceding chapter, to various areas of transportation engineering, such as the evaluation of the service quality of a transportation facility, user satisfaction with a traveler information system, and the evaluation of the degree of safety of a transportation system. The principal focus of this effort will be related to transportation user perception. One possible means for developing a fuzzy approach to assess transportation user’s perception through the proposed study consists of the following four tasks:

- Task 1 - Develop a general methodology using fuzzy sets for evaluating user perception in transportation engineering.
- Task 2 - Apply the method to some aspects of transportation facility design or operation as application case studies.
- Task 3 - Revise the general methodology using the experience gained through the application case studies.
- Task 4 – Validate the proposed methodology and the fuzzy results

Even though some transportation studies have already used the concept of the fuzzy sets, there is a need to develop generalized methodologies for applying fuzzy sets to the study of transportation user’s perception, such as the determination of membership functions, design of the experimental study, analysis of user linguistic perception, and development of the fuzzy inference system. For developing the general fuzzy methodology regarding these issues, a review of fuzzy approach as used in other fields (as previously addressed in the literature review, e.g., evaluation of business service quality, decision making process, or studies of operator workload in industrial engineering settings) preceded the current study. The approaches using fuzzy sets vary as significantly as the topics, and they need to be modified for application in the analysis of
transportation facilities for which user perception is taken into account. Figure 3-1 shows the entire procedure for the proposed study.

Figure 3-1: Methodology Flow Chart.
3.1 Development of a General Methodology (Task 1)

The first step, the development of a general methodology, included the modification of previously used fuzzy approaches that could be applied to the investigation of transportation user perception. Modification of the existing fuzzy approaches follows three mechanisms. First, basic information about fuzzy set theory was reviewed. Fuzzy set theory has been applied in many areas and is comprised of many elements, including the following: fuzzy relation, fuzzy numbers, fuzzy reasoning, fuzzy inference system, and fuzzy control. The investigation and understanding of these elements is necessary to develop a methodology for applying fuzzy sets to transportation user perception. Second, some of the fuzzy approaches that have been used in other fields were investigated to determine if these methods could be applied directly to the study of transportation user perception. If some or all of these approaches were applicable, then a subset of candidate methods was selected for further development. Even though most of the studies employing fuzzy sets exploited the capability of the fuzzy sets to represent and analyze uncertain concepts or values, which were the main characteristics of transportation user perception, some revision was required prior to the use of the fuzzy sets in interpreting transportation user perception. Finally, the particular fuzzy approach to be used for analyzing transportation user perception was developed taking into consideration the results of the two previous processes.

To develop the fuzzy approaches to interpret transportation user perception, the following four procedures were investigated:

- Consideration of the feasible and appropriate types of fuzzy methods from the various fuzzy approaches
- Investigation of the appropriate methods to construct the membership functions
- Design of the experiment and data set forms for the fuzzy approach
- Development of the appropriate fuzzy inference system
Additionally, the compatibility of transportation experts’ perception with the public perception was examined.

3.1.1 Feasible and Appropriate Types of Approaches for Analyzing Transportation User Perception using Fuzzy Set Theory

The development of the general methodology was conducted based on pre-selected fuzzy methods that were chosen because of their feasibility and appropriateness of their use to this type of analysis. There were many different types of application of fuzzy sets and not all of these methods can be applied in the study of transportation user perception. These methods were investigated and their applicability was determined through a review of various types of fuzzy techniques and related previous studies. The various types of fuzzy techniques that have been applied and should be reviewed were the fuzzy aggregation method, intelligent fuzzy control, fuzzy inference system, fuzzy regression, fuzzy cluster analysis, and hybrid fuzzy set technique.

3.1.2 How to Construct Membership Functions

Determination of the membership function is the most important procedure in the fuzzy approach. It is closely related to the data collection scheme and the experimental design. The methods for developing the membership function can generally be classified into three approaches: constructing a fuzzy membership function through intuition, constructing a fuzzy membership function through experiments, and constructing a membership function from a given data set. To analyze transportation user perception with the fuzzy approach, the data collection and experimental study design should be modified slightly to determine an appropriate membership function as mentioned above. Methods of determining the membership function using a data set that was already in hand, collected by conventional means, including survey or experimental study, were also investigated.
3.1.3 How to Design the Experiment for the Fuzzy Approach

The common way to construct a membership function representing human perception is conducted through an experimental study. When using fuzzy sets for the analysis of transportation user perception, the design and conduct of the associated experiments is a significantly important process. Designing an experiment for the fuzzy approach is different from an ordinary experimental design because the fuzzy experiment collects quantitative and qualitative data elements as well as the reasoning behind the subjects’ qualitative judgments, all which are necessary for the application of fuzzy set theory. In addition, the formation of the data set should be geared towards the application of fuzzy set theory. As the features of data set affect the selection of the method of determining the membership function, the development of the design of the experimental study and the form that the data set will take should precede these others steps.

3.1.4 Developing the Fuzzy Inference System

The fuzzy inference system, also called fuzzy logic, is one of the most common fuzzy techniques. To apply the fuzzy inference system in the analysis of transportation user perception, several issues should be considered, such as the structure of the fuzzy inference system and the methods used to create fuzzy rules. Generally, user perceptions regarding transportation systems are influenced by many factors consisting of complicated mechanisms. Given this circumstance, selection of an appropriate structure for the fuzzy inference system is an important step. Another issue deals with the methods used to create the fuzzy rules. Fuzzy rule generation is one of the core procedures in the development of a fuzzy inference system. There are various methods to generate the fuzzy rules. These included the use of experts’ opinions, the use of functional relationships between input and output variables, or the use of other intelligent techniques, such as an artificial neural network or a genetic algorithm. The determination of which fuzzy rule generation method is the most applicable for the study of transportation user perception is also an important step. Therefore, some thought was
given to how to do this and new methods to generate fuzzy rules were developed as part of this study. They are introduced in the chapter that covers the development of the general fuzzy approach, chapter 4.

3.1.5 Comparison of Expert Perception with Public Perception

For problems related to human perception, surveys and experiments are generally conducted to provide data that can be used to conduct a specific fuzzy application. These surveys and experiments are usually conducted using members of the general public, but they can also use a group of experts instead. In the fuzzy application of the study of transportation user perception, the selection of groups of participants is a critical issue. The opinions of experts regarding a transportation system are not always the same as the opinions of users. Also, the perceptions of a transportation system that researchers would like to investigate are the perceptions from actual users, not those from experts who do not actually use the system. Under these circumstances, comparisons of experts’ perceptions with public perceptions were conducted to determine if they are statistically identical or different.

The general methodology developed through the procedures described above was applied to studies of user perception as they relate to transportation. Through the application, limitations to and problems associated with the developed fuzzy approaches and their details were found. These findings are used to make further improvements to the fuzzy approaches to analyze transportation user perception.

3.2 Application Studies (Task 2)

After developing the general methodology, it was applied to the assessment of the design or operational elements of some transportation facilities. For the application case studies, various methods were used for each step of the fuzzy techniques selected for the analysis
of transportation user perception. Their strengths, weaknesses, and suitability for application to transportation user perception were assessed as well. This included various experimental methods, construction of membership functions, and fuzzy analysis approaches. While the application studies were in progress, limitations to and problems associated with the developed general methodology were found. These findings were used to make further improvements to the methodology. After this feedback procedure, the final methodology to apply the fuzzy technique for the analysis of transportation user perception was completed.

3.2.1 Evaluation of VMS Service Quality

One of ways to investigate driver satisfaction with the service quality of a VMS is to use a survey examining motorists’ satisfaction with the content and accuracy of the information provided by a VMS. The survey instrument used to evaluate the quality of service provided might not yield results that represent the satisfaction that drivers truly perceive in the field because these techniques cannot represent, with great fidelity, the variety and complexity of human perception. Another problem with using a survey method is the difficulty of describing the survey results quantitatively and objectively because the surveys primarily use linguistic terms rather than exact quantitative scales to evaluate a subject’s response. These linguistic terms are determined by subjective human decision making processes. To solve these problems, results of a pre-existing survey of VMS service quality were re-analyzed using fuzzy sets.

The data on VMS service quality came from an evaluation of an advanced traveler information system (ATIS) used by the Pennsylvania Turnpike. This evaluation was conducted by researchers at the Pennsylvania Transportation Institute (Patten et al. 2003). For the driver satisfaction study, they employed a mail back survey that was returned by a total of 2,417 respondents (1,528 motorists and 889 truckers). In that part of their study, they investigated how drivers’ perceive the service quality of the ATIS. They focused on three traveler information system elements: VMS, highway advisory radio (HAR), and telephone service. To evaluate the service quality of each of those
system elements, questions in the survey consisted of five scales of perception: strongly disagree, disagree, neither agree nor disagree, agree, and strongly agree. From these data, two membership functions will be constructed using two different additional surveys: interval estimation and pair-wise comparison in order to re-analyze the survey results.

3.2.2 Evaluation of Median Safety

Another application topic related to user perception was an evaluation of the safety of transportation facilities. Traditionally, the evaluation of highway safety is conducted using historical crash data. However, the degree of road safety perceived by the user also has an important meaning. For example, suppose a roadway segment did not have any crashes for a period of five years. Assume also that most of drivers who used the roadway segment said that it was very dangerous place. The degree of safety of the segment could be considered to be very low in spite of the fact that there were no crashes for the last five years.

A transportation expert may be asked to provide an opinion for various purposes using a variety of means. Most studies aggregate the opinions using simple statistical methods. However, this aggregation can ignore the unique characteristics of and the decision criteria used by an individual expert because they use linguistic information and their own subjective decision criteria to formulate and express their opinions. Furthermore, it is difficult to validate those subjective opinions. In a 2000 study of median safety, factors that influence median safety on interstates and expressway were investigated (Mason et al. 2001). The researchers surveyed 23 transportation experts to collect their opinion regarding which factors most influence median safety. They investigated four major factors: geometric elements, percentage of heavy vehicles, median width, and average daily traffic (ADT). Perceptions dealing with the condition of these four factors regarding safety may measure the degree of safety that users perceive. As this measurement of the degree of safety is based on subjective data, a fuzzy approach is an appropriate method. The fuzzy inference system, developed as part of this work,
can then be used to estimate the likelihood of a median crash occurring within an individual highway segment.

3.3 Validation of the Analysis Results of Transportation User Perception based on Fuzzy Approaches

In scientific research, validation of a new methodology or the results from the methodology is an important procedure. However, it is one the most difficult aspects in a study related to human perception because of the difficulty in obtaining a true value of human perception to be compared in the validation process. There is no unique true value of a certain perception. Given this difficulty, a traditional validation of the developed methodology is extremely difficult to perform; however, an evaluation of the efficacy of the technique would be very meaningful and add to the overall value of this research. In this study, two possible methods to validate the fuzzy results were proposed. These methods were a “direct validation method” and an “indirect validation method.” These two validation methods were applied to different transportation problems. To apply the direct validation method, an experimental study dealing with evaluating the service quality of signalized intersections was conducted. The application of the indirect validation method was performed based on a review of observed cross median crash (CMC) data.
CHAPTER 4
DEVELOPMENT OF A GENERALIZED FUZZY APPROACH FOR ANALYZING TRANSPORTATION USER PERCEPTION

4.1 Introduction

This chapter explains how to apply fuzzy set theory to evaluate transportation user perception. Through this chapter, the elements of the generalized fuzzy approach for analyzing transportation user perception, which has been developed as the primary objective of this study, are described, such as the construction of fuzzy membership functions, determination of a structure of a fuzzy inference system, and fuzzy rule generation. Each element of the application of fuzzy set theory was developed based on two different types of fuzzy set approaches: use of fuzzy aggregation methods and use of fuzzy inference systems. Critical elements of the fuzzy application include a design of the experiment, construction of the appropriate database, construction of fuzzy membership functions, and a design of an overall structure of the fuzzy applications. These elements are explained later in this chapter. Section 4.2 outlines the concepts behind the two proposed approaches. The following sections specifically explain how to apply the fuzzy approaches for evaluating transportation user perception, including how to construct fuzzy membership functions and how to conduct experiments to construct fuzzy membership functions (section 4.3); how to generate fuzzy rules and how to create the appropriate structure of the fuzzy inference system (section 4.4).

4.2 Two Approaches for Analyzing Transportation User Perception Using Fuzzy Set Theory

Fuzzy set theory has been applied in many studies using different types of fuzzy techniques, such as fuzzy inference system, fuzzy aggregation method, fuzzy regression, and fuzzy clustering. Among these techniques, the fuzzy aggregation method and fuzzy
inference system are the most appropriate fuzzy techniques for use in the evaluation of transportation user perception.

Fuzzy aggregation is a method of aggregating subjective data based on extended algebraic operations with fuzzy numbers. This method is usually applied by the concept of $\alpha$-cuts representation of fuzzy numbers. It has been applied for multiple criteria decision making and aggregation of experts’ opinions. Subjective public or expert opinions regarding certain alternatives or services are more easily represented by linguistic terms than by a numerical value. In the fuzzy aggregation method, the subjective opinions represented by linguistic terms are transformed into fuzzy membership functions to be used in extended fuzzy operation algebras. Usually the aggregation is conducted by using many criteria and their different fuzzified weights. The strength of this method in evaluating transportation user perception is that it allows for the use of a linguistic “value,” which is known as the most efficient way to represent a person’s perception, and it aggregates the perceptions without losing the variety of each individual’s decision making characteristics. Another advantage of this method is that there is no need to have numerical inputs that would need to be fuzzified. A more detailed explanation regarding the application of this method for transportation user perception is provided in section 4.2.1.

The fuzzy inference system is one of the most commonly applied fuzzy techniques. It is a deductive process for mapping from given inputs to outputs using fuzzy logic. This method has been commonly used for intelligent control systems and expert systems. To apply this method for transportation user perception, there is a need for numerical inputs that will be fuzzified and mapped with outputs through fuzzy rules. However, if the necessary conditions are satisfied, this method can produce better results than conventional analyses of user perception because human, especially expert, knowledge and experience can be applied in the process of fuzzy rule generation. A more detailed explanation regarding the application of this method for transportation user perception is given in section 4.2.2. Table 4-1 shows the comparison of the two fuzzy approaches for analyzing transportation user perception.
Table 4-1: Comparison of the Two Fuzzy Approaches for Analyzing Transportation User Perception.

<table>
<thead>
<tr>
<th>Issue</th>
<th>Fuzzy Aggregation Method</th>
<th>Fuzzy Inference System</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Main procedure</strong></td>
<td>An aggregating process for subjective responses based on several criteria using extended fuzzy operation algebra</td>
<td>A deductive process of the mapping from given inputs to outputs using fuzzy logic</td>
</tr>
</tbody>
</table>
| **Most critical steps**       | - Constructing fuzzy membership functions  
- Estimating weights of criteria  
- Selecting the most appropriate aggregation method  
- Selecting input variables | - Constructing fuzzy membership functions  
- Fuzzy rule implication  
- Selecting input variables |
| **Input variables**           | - Linguistic values  
- Same ranges for all input variables (0.0 to 1.0) | - Numerical data fuzzified  
- Different ranges based on the magnitude of the input variables |
| **Weights of input variables (criteria)** | - Necessary  
- Use of weights is the only way to consider the various importance levels of the input variables | - Not necessary  
- The different importance level of each input variable can be considered through the fuzzy rule generation step |
| **Consequence Variables**     | Not necessary                                                                           | Necessary                                                                              |
| **Final output**              | Calculated degree of perception for certain aspects ranging from 0.0 to 1.0 (e.g. degree of satisfaction with VMS service) | Deduced degree of perception for certain aspects with no range limitation               |
| **Fuzzy Membership Function** | - Fuzzy membership functions for linguistic scales  
- Fuzzy weights of each criteria | - Fuzzy membership functions representing input variables  
- Fuzzy membership functions representing output variables |
| **Need of true value**        | Not necessary                                                                           | Necessary                                                                              |
| **Assistant technique**       | - Fuzzy weighted average  
- Similarity  
- Entropy  
- Saaty’s pair-wise comparison | - Neural network  
- Fuzzy clustering technique  
- Genetic algorithm |
4.2.1 Evaluation of Transportation User Perception Using Fuzzy Aggregation Method

In many research studies, user perceptions of certain subjects are evaluated using linguistic scales with a various numbers of descriptors. For example, a five descriptor linguistic scale could be comprised of the terms: strongly unsatisfactory, unsatisfactory, neither unsatisfactory nor satisfactory, satisfactory, and strongly satisfactory. However, most studies calculate only simple descriptive statistics, such as percentage or frequency, to analyze these types of responses. The proposed method, based on the fuzzy aggregation method, enables one to analyze and aggregate the subjective responses without losing the variety of individual decision making characteristics.

Evaluation of transportation user perception using the fuzzy aggregation method is based on the results of user surveys. This evaluation method basically has two steps: a survey with linguistic scales and an analysis of the survey responses using fuzzy aggregation methods. In the survey process, there are three types of questions that need to be asked. The first type of question is to evaluate transportation user perception regarding certain subjects using the linguistic scales relative to different criteria. The second type of question is to estimate a respondent’s perception level for each linguistic scale and construct fuzzy membership functions corresponding to the perception level. The last type of question is to estimate the relative importance level of each criterion. Prior to posing these three types of questions, several issues should be resolved as the survey questions will be based on the resolution of these issues.

- What and how many criteria will be used to evaluate transportation user perception?
- How many descriptors will be used for the linguistic scales and what corresponding linguistic terms will be used in the survey?
- What method for constructing fuzzy membership functions will be used?
- Which weight estimation method will be used?
Deciding which of the criteria to use in evaluating transportation user perception is the most critical step in the proposed method. The criteria are chosen after a sufficient literature review and with reasonable engineering judgment.

Surveys of the second and third type of questions are a preceding procedure for analyzing the responses through the fuzzy aggregation method. Two different types of fuzzy membership functions are determined using the responses of the second and third type of questions. Usually an interval estimation method for constructing fuzzy membership functions representing the respondents’ perception level for each linguistic scale is most appropriate and is commonly used (Juang et. al. 1992, Lee et. al 2005).

Generally, the pair-wise comparison methods are known to produce a significantly more precise weight of each criterion (Juang et. al. 1992). Among the various pair-wise comparison methods, Saaty’s pairwise comparison method is the most commonly applied method to estimate relative importance of criteria (Lee et. al 2005). The various methods to construct fuzzy membership functions will be explained in the later chapter 4.3

Fuzzy membership functions representing the response’s perception level for each linguistic scale, and fuzzy weights for criteria are used to calculate a fuzzy weighted average that represents the evaluated individual transportation user perception based on criteria (Eq. 4.1)

\[ P_j = \frac{\sum_{k=1}^{n} (w_k \otimes A_{jk})}{\sum_{k=1}^{n} w_k} \]  

where

- \( P_j \) = the certain transportation user perception of a participant \( j \),
- \( k \) = the criterion of the transportation user perception,
- \( w_k \) = the normalized fuzzy weights of criteria \( k \) (\( \sum w_k = 1 \)),
- \( A_{jk} \) = the fuzzy membership function representing the individual transportation user perception based on criterion \( k \), and
- \( \sum_{k=1}^{n} \) and \( \otimes \) = fuzzy operations using \( \alpha \) – cut interval analysis.
This concept, the fuzzy weighted average method, was developed by Dong and Wong to be an improvement over classical weighting methods (Dong and Wong 1987). The fuzzy weighted average is based on extended algebraic interval operations and the concept of $\alpha$ – cuts representation of a fuzzy number. The use of the interval operation was also introduced in the same study (Dong and Wong 1987) and has been commonly used to compute a fuzzy weighted average. The intervals of two fuzzy numbers corresponding to particular $\alpha_i$ are operated using the following algebraic equations (Eq. 4.2).

$$[a_i, b_i] = [a_i + c_i, b_i + d_i]$$

$$[a_i, b_i] \times [c_i, d_i] = [\min(a_i, c_i), \max(a_i, c_i), \min(b_i, d_i), \max(b_i, d_i)]$$

$$[a_i, b_i] \div [c_i, d_i] = [a_i, b_i] \times [1/c_i, 1/d_i]$$

Eq. 4.2

For applying $\alpha$ – cuts, three $\alpha$-values are usually used, including 0, 0.5 and 1, to find the intervals.

In many cases, an overall group opinion is required rather than many different individual opinions. In conventional approaches, statistically aggregated values (including mean, mode, and median) are used to represent the overall group opinion. However, the variety of individual perception from the personal characteristics and situational characteristics can be ignored in these simple statistical values. To overcome this problem, two fuzzy methods to aggregate individual perception and evaluate the overall group’s opinion are commonly used. The first way is to use the concept of an “arithmetic mean” of fuzzy numbers. This fuzzy mean is calculated using a fuzzy average operation based on the “$\alpha$-cut” concept of fuzzy sets and an interval analysis. The second way is to use a similarity measure. Hsu and Chen proposed a method to aggregate individual fuzzy opinions into a group fuzzy consensus opinion using a similarity measure (Hsu and Chen 1996). They estimated the index of consensus of each expert to the other experts using a similarity measure. The experts’ opinions are aggregated using the index of consensus and the importance of each expert. In this thesis, the detailed explanations concerning these two methods are not provided.

Figure 4-1 shows the entire procedure of evaluating transportation user perception using
fuzzy aggregation methods. An example of applying this method will be illustrated in chapter 5 using a case that evaluates a driver’s satisfaction of variable message signs.

Figure 4-1: The Procedures of Evaluating Transportation User Perception Using Fuzzy Aggregation Methods.
4.2.2 Evaluation of Transportation User Perception Using Fuzzy Inference System

The evaluation of transportation user perception using a fuzzy inference system is a method that is based more on experts’ experience and knowledge than the previously discussed fuzzy aggregation method. In this method, the fuzzy rule generation relies more on the experts’ experience and knowledge. The fuzzy rules are generated from the experts’ opinions or results of related empirical studies. When fuzzy inference systems are used in other fields, such as intelligent control, the fuzzy rule generation is based on a functional relationship between two groups of numerical variables, input variables, and output variables. The fuzzy rule generation is normally conducted through a partition-based technique using functional relationships between input and output variables.

However, an output variable does not always exist in the database when considering problems related to transportation user perception. Also, the functional relationship between input variables and an output variable is not well defined. For example, the degree of highway safety perceived by drivers can be evaluated using criteria, such as: lane width, operating speed, horizontal alignment, or other geometric features of the roadway segment. In this example, these criteria are used as input variables (i.e., antecedents) and the degree of highway safety perception is used as an output variable (i.e., consequence) in the fuzzy inference system. The degree of highway safety perception can be defined as “the degree perceived by a driver regarding how safe a certain roadway segment is.” This value ranges from 0.0 to 1.0. However, the degree of highway safety perception is a variable having no true value because the perception is differentiated by individual drivers’ characteristics and the situational characteristics they encounter when they drive. In other words, the degree of perception regarding the same roadway segment can differ between drivers, and the individual degree of perception about a particular roadway segment can differ by the situations the driver experiences.

Under these circumstances, the functional relationship between these criteria and the degree of highway safety perception of individual drivers is difficult to estimate. To solve this problem, a new method for fuzzy rule generation is suggested in this study. This new method is based on the fuzzy aggregation and partition-based techniques.
apply this method, fuzzy membership functions and fuzzy weights for criteria (i.e., an input variable) are constructed, and a fuzzy aggregated value for all combinations of the criteria is calculated using these two fuzzy values. These combinations provide an overall representation of the criteria. Using the results of the fuzzy aggregation, the fuzzy partition and rule mapping procedures are conducted. A more detailed description will be explained later in chapter 4.4.2.

When evaluating transportation user perception using the fuzzy inference system, two initial steps are required. These are: deciding on the input variables and output variables and determining the structure of the fuzzy inference system. The decision regarding which criteria to use as input variables is an extremely important step. If inappropriate criteria are selected or if key criteria, which might significantly influence the output variables, are omitted, then the final output (i.e., a certain perception of the transportation system by the user) cannot be appropriately evaluated using the fuzzy inference system. The fuzzy inference system can be configured into one of two structures, a conventional structure and a hierarchical structure. A conventional fuzzy inference system is constructed with one level (i.e., a non-hierarchical structure), while a hierarchical fuzzy inference system is constructed with more than one level (i.e., a hierarchical structure). A hierarchical fuzzy inference system is one of the ways to avoid the “rule explosion problem” inherent in many multivariable fuzzy inference systems. Since transportation user perception is usually affected by many factors, a multivariable fuzzy inference system is more suitable, and a hierarchical fuzzy inference system is more appropriate (Lee et al. 2006). A more detailed description regarding the limitation of the conventional fuzzy inference system and the hierarchical fuzzy inference system is provided in chapter 4.4.1.

Once the variables and structure have been chosen, the fuzzy membership functions are constructed, and the fuzzy rules are generated to completely build the fuzzy inference system. There are three types of fuzzy membership functions that can be used. These three types of fuzzy membership functions are as follows: the fuzzy membership functions for each input variable, the fuzzy weights to be applied in the fuzzy aggregation process, and the fuzzy membership function for an output variable. The fuzzy rules are generated by various methods, which are described later in chapter
4.4.2. Figure 4-2 shows the entire procedure for evaluating transportation user perception using fuzzy inference systems. An example of the application of this method, incorporating transportation experts’ opinion of median safety, will be provided in chapter 6.

Figure 4-2: The Procedures of Evaluating Transportation User Perception Using Fuzzy Inference Systems.
4.3 Fuzzy Membership Functions for Analyzing Transportation User Perception

The development of the fuzzy membership function is the most important step when following a fuzzy approach as it allows the use of fuzzy techniques in analyzing transportation user perception. There are many classes and different types of fuzzy membership functions. In this section, three of these classes of fuzzy membership function and the methods to construct them will be explained.

4.3.1 Three Classes of Fuzzy Membership Function for Analyzing Transportation User Perception

There are three classes of fuzzy membership function that can be applied in the study of transportation user perception. The first is used to represent how people form their perception through certain levels of qualitative variables such as agreement or satisfaction. For example, assume that a person is supposed to provide their own perception regarding the assessment of service quality of variable message signs (VMS) based on the five point scale: strongly unsatisfactory, unsatisfactory, neither unsatisfactory nor satisfactory, satisfactory, and strongly unsatisfactory. When the respondents determine their level of satisfaction, they determine and use their own thresholds to decide which of the five levels to choose. Since thresholds for each individual’s satisfaction are different, a simple aggregation of the response is restricted in its ability to explain the overall perception. This class of fuzzy membership function is good at explaining various peoples’ decision making thresholds and trends. The second class of fuzzy membership function is used to represent the relative importance of different criteria that will be used in evaluating a certain transportation user perception, such as service quality or the degree of highway safety. For example, the service quality of VMS may be evaluated by considering the following six criteria: visibility, legibility to read, comprehension of message displayed, accuracy of information, usefulness of information, and correspondence between information displayed and that expected by drivers. These six criteria may not have the same level of importance for different users when evaluating the service quality of VMS, and the perception of this relative
importance level of each criterion will be different for each individual. The third class of fuzzy membership function is used to represent the level of effectiveness of each criterion, for example, good, fair, and poor effectiveness of median width on safety. This class of fuzzy membership function is similar to the first class; however, the first class can only be determined through the use of a survey while this third class can be constructed by reviewing information relevant to the problem being considered as well. This information might be garnered from previous research that investigated the relationship between a specific criterion and the investigated qualitative variable, for example, VMS visibility and service quality or median width and safety. Figure 4-3 shows examples of the three classes of fuzzy membership functions.
a) Fuzzy Membership Functions for Five Linguistic Scales

![Graph showing membership functions for strongly disagree, disagree, neither agree nor disagree, agree, and strongly agree.]

b) Fuzzy Membership Functions for Weights

![Graph showing membership functions for different criteria with different symbols.]

c) Fuzzy Membership Functions for the Effects of Criteria on Transportation User Perception.

![Graph showing membership functions for poor, fair, and good conditions based on median width.]

Figure 4-3: Examples of the Three Classes of Fuzzy Membership Functions.
4.3.2 Determination of Fuzzy Membership Functions

A fuzzy membership function in fuzzy application studies allows for the representation and analysis of subjective and ambiguous human perceptions. The determination of the fuzzy membership function is the most important procedure in the fuzzy approach for studying transportation user perception. Dombi (1990) indicated the importance of the appropriate measurement of the fuzzy membership functions as follows:

In the development of fuzzy set, a lot of articles were written dealing with different generalization of the operators proposed by Zadeh, and only a few researchers have concentrated on the topic of membership function. …… All problems arising in the theory of fuzzy sets are due to the lack of our knowledge or the interpretations of ‘fuzzy.’ It is dangerous to neglect clarifying where the membership function came from, because it is one of the most important aspects in the application.

Ragin (2000) introduced several steps to measure the degree of membership (i.e. what he referred to as “the fuzzy membership score”) as follows:

a. To specify the relevant domain of the assessment
b. To define the fuzzy sets that follow from the concepts guiding the investigation
c. To determine the type of fuzzy sets that is feasible for each concept
d. To determine the likely range of fuzzy membership scores
e. To identify empirical evidence that is appropriate for indexing fuzzy membership scores
f. To translate empirical evidence into scores

Based on Ragin’s steps, the steps used to construct fuzzy membership functions for transportation user perception are recommended as follows:

a. Define the problem(s) related to transportation user perception

Problems related to the transportation user perception in question, such as service quality or safety of the transportation facilities, are defined prior to the construction of the fuzzy membership function. Then, the relevant user perception to be evaluated is specified. For example, after defining the problem to be analyzed as “perception regarding traffic congestion,” the analyst could
specify the perception of traffic congestion by type of roadway or regional features. A driver’s perception regarding traffic congestion in rural areas is different from that in large city, such as New York. As another example, the fuzzy membership function used to represent the effect of horizontal curvature on speed is not same as the effect horizontal curves on safety. Therefore, an analyst should specify the perception and the transportation system that will be analyzed.

b. Collect the data used to determine fuzzy membership functions
The data used in the determination of fuzzy membership functions is information dealing with how much the given input variables influence a certain perception to be analyzed (i.e., output variable). For example, the fuzzy membership function in Figure 4-3 (c) shows how much various median widths influence highway safety. These data could be collected from an experiment or from other sources (e.g., research literature). The types of experiments that can be used will be described in section 4.3.2.2.

c. Determine the type of fuzzy membership functions and the number of descriptors
The type of fuzzy membership function and numbers of descriptors in each fuzzy membership function, for example, three descriptors including “Poor”, “Fair,” and “Good,” can influence the final output considerably. As mentioned in section 2.2.4, there are numerous types of fuzzy membership functions, which include the following: triangles, trapezoids, bell-shape curves, S-shape curves, Π-shape curve, Gaussian, and sigmoid function. The type of fuzzy membership function is determined through a review of the available data and literature; and a review of the study to be conducted. The following guidelines can be applied as a general set of rules to select the appropriate type of the fuzzy membership function.

- Triangular and trapezoidal functions are the simplest types of fuzzy membership function. Due to their simple formulas and computational efficiency, both membership functions have been used popularly and extensively in fuzzy set applications.
- Between the triangular and trapezoidal functions, the trapezoidal function is better than the triangular function if there is more variance in the data set.

- Some curved membership functions such as bell curves, Gaussian, and sigmoid function, are better if there are large numbers of data. They can produce more accurate results.

The number of fuzzy membership function descriptors selected is a function of the analyst’s judgment based on a review of the available data and the relevant literature. Fuzzy membership functions with a small number of descriptors are easily understood but have difficulty in giving a distinguishable explanation of the specific perception. On the contrary, fuzzy membership functions with a large number of descriptors give an easily distinguishable explanation of the specified perception but are difficult to understand. Usually, as the number of fuzzy membership function descriptors for a variable in the antecedent and consequent parts increases, the range of the defuzzified final output increases as well.

d. Determine parameter values for each fuzzy membership function

As mentioned in the section 2.2.4, fuzzy membership functions are specified by three or four parameters. Generally, the parameters to be specified correspond to 0.0, 0.5, or 1.0 degree of the membership, \( u_A(\delta) \). The triangular and bell-shape curve functions are specified by three parameters, while the Gaussian and sigmoid functions are determined by only two parameters. A trapezoidal function consists of four parameters. The various parameters control the exact shape of the membership function as well as the function values. The desired membership function is obtained by the selection of the appropriate parameters. Parameter values are determined through the analyst’s intuition, through experiments, or by the given data. Determination of the parameter values is an essential step to determine the appropriate fuzzy membership function. The degree of membership for a certain case is defined by the specified parameters. The degree of membership indicates the degree to which a relevant case belongs to the set.
that the analyst uses to describe and analyze the specific case. For example, medians having a width of less than 30 feet have the full degree (i.e. a value of 1.0) of “belonging” to the set of “Poor” median conditions for highway safety and have the non degree of belonging to the sets of “Fair” or “Good” median conditions for highway safety (see Figure 4-3).

Based on the aforementioned procedures, the methods of constructing fuzzy membership functions can generally be classified in terms of how the needed information is gathered. This can be categorized into the following three approaches: constructing the membership function through intuition, constructing the membership function through experiments, or constructing the membership function from supplied data sets. Selecting which method to use to construct membership functions depends on many conditions including the study characteristics and the available data set associated with the study. In many fuzzy set applications; however, the membership functions have been determined by the analyst’s own innate intelligence or from other related studies without any concern of what the topic is. In applying fuzzy sets to transportation engineering, the membership function should be determined through understandable and acceptable procedures.

When using experiments to construct the fuzzy membership functions, several different experimental methods can be applied. The following six experimental methods can be used: polling, direct rating, reverse rating, interval estimation, membership function exemplification, and comparison including absolute or pair-wise comparison (Dubois and Prade 2000). Another type of the experimental method that can be used to construct fuzzy membership functions is a scaling method. Alternatively, there is generally a large amount of numerical data that can be used to construct fuzzy membership functions within the transportation engineering field. Also in many cases, conducting additional experiments for the construction of fuzzy membership functions is not feasible within the constraints of the research schedule or budget. Under these situations, fuzzy membership function can be constructed using a supplied data set.

If a perception data set is not available, the fuzzy membership function can be constructed using surrogate data sets, for example, the crash rate for the degree of safety perceived. Usually the third class of fuzzy membership function, which is the fuzzy
membership function for the effects of criteria on transportation user perceptions, is suitable to be determined using this method. There are four methods employed to construct fuzzy membership functions from supplied data sets including the following: use of the basic statistical method based on the plot of a normalized relative frequency function and histogram, a fuzzy cluster, a neural-fuzzy technique, and a genetic algorithm. Use of the three latter “intelligent techniques” is commonly recommended as a more reliable and appropriate approach. These methods are restricted in the study of transportation user perception due to the characteristics of the study. These methods are performed using the relationships between input and output variables. Since there is generally no numerical output variable, which usually is a unique perception of transportation services or facilities, applying these techniques are restricted. Therefore, a further detailed explanation of these methods, including how to apply them for the study of transportation user perception, is not provided in this section.

4.3.2.1 Constructing Fuzzy Membership Functions through Intuition

The method based on analysts’ intuitive judgment is the most common method to determine fuzzy membership functions. In this method, analysts employ their own knowledge and experience, and review the results of relevant literature to compose fuzzy membership functions. For example, insufficient median widths can cause “median-related” crashes on the roadway. The median widths could be classified into one of three descriptors, for example poor, fair, or good. The fuzzy membership functions used to represent the effect of the median width on highway safety can be determined using these three descriptors. To determine the fuzzy membership functions, analysts can partition the median width into three classes and form the fuzzy membership functions based on their knowledge and experience. Also, the analysts can review the relevant literature, typically empirically based studies. Then, the analysts can determine finally the three classes of median width and construct the fuzzy membership functions. To have fuzzy membership functions that would be more acceptable generally to other professionals, it is best to base the formulation of these functions on an amalgam of information based on the relevant literature in the field. In transportation engineering applications, there are
many books that provide guidelines for the design and operation of transportation facilities. These include such examples as the American Association of State Highway and Transportation Officials’ (AASHTO) *A Policy on Geometric Design of Highways and Streets (the Green Book)*, AASHTO’s *Roadside Design Guide*, and *Highway Capacity Manual (HCM)*. These resources are very useful in constructing reasonable and acceptable fuzzy membership functions. This is because they are based on the results of a number of previously conducted empirical studies and because most transportation engineers already accepted the information therein. Figure 4-4 shows a sample of resources that could be used to construct the fuzzy membership functions for median safety. A more detailed description regarding the construction of the fuzzy membership functions will be given in the chapter 6.

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**Figure 4-4:** Potential Resources to Determine the Fuzzy Membership Functions for Median Safety.
4.3.2.2 Constructing Fuzzy Membership Functions through Experiments

In this section, the six experimental methods, introduced previously, used to construct fuzzy membership functions are described. To illustrate each method, a sample question of the type generally used with each method is provided. Another question illustrating a perception regarding the service quality of signalized intersections is given to show applicability of the six experimental methods to transportation engineering fields. In this illustrative question, three descriptors (i.e. poor, fair, and good) of the fuzzy membership functions used to represent the service quality of signalized intersections as perceived by users are utilized. In the description, $\delta$ represents the elements or objects to be analyzed, and $x_\delta \in X_\delta$, represents the fuzzy values or indicators. $A$ is the term of a linguistic variable for the fuzzy membership function to be constructed. For example, if the fuzzy membership function used to represent the warmness of a room is constructed, $\delta_i$ indicates room $i$, and $x_{\delta_i}$ indicates the room temperature. Three descriptors for the linguistic terms can be defined as follows:

$$A_1 = \text{Cold}, A_2 = \text{Medium}, \text{and } A_3 = \text{Hot}$$

- **Polling**

The first of the six experimental methods is a polling survey technique, which was used previously by Labov (1973). This experimental method is also called the “Horizontal Method,” and it is based on the concept that fuzziness arises from interpersonal disagreement. In other words, the degree of membership, which fuzzy membership functions represent, is determined by the concept that individuals are different. The fuzziness is created from this difference. In this method, analysts should know the value of $x_\delta$ for each case and keep this information hidden from the subjects in the experiment. The experiment will generally be conducted using following question:

“Do you agree that $\delta$ is $A$?”
To apply this type of question in the evaluation of the service quality of signalized intersections as perceived by drivers, the following questions can be applied:

“Do you agree that the service quality of signalized intersections $i$ is poor?”
“Do you agree that the service quality of signalized intersections $i$ is fair?”
“Do you agree that the service quality of signalized intersections $i$ is good?”

Individual drivers are asked these questions, and the proportion of positive answers is used to construct the fuzzy membership function. In other words, the value $u(x_i\delta)$ is directly obtained as the proportion of positive answers over the total number of answers as seen in the following equation (Eq. 4.3):

$$u_\delta(x_i) = \frac{P(X_i)}{N}$$

where $u_\delta(x_i\delta)$ is the degree of fuzzy membership

$P(X_i)$ is the number of positive replies

$N$ is the total number of responses

Polling is one of the simplest ways to construct fuzzy membership functions, and it has been used in many previous studies (Labov 1973, and Hersh and Carmazza 1976). This method, along with interval estimation, is known as an adequate method in determining collective fuzzy membership functions that have more than one descriptor such as poor, fair, and good (Sancho-Royo and Verdegay 1999).

- **Direct Rating**

The second method involves the use of a direct rating technique. This method is one of the most straightforward ways to measure a membership function (Dubois and Prade 2000). It is conducted based on the concept that vagueness arises from individual subjective uncertainty (Sancho-Royo and Verdegay 1999). In this method, $\delta$ is shown to the subjects, and subjects are typically asked to state their opinion regarding the given variable. The following question is generally used:
“How $A$ is $\delta$?”

To apply this type of question to the evaluation of the service quality of signalized intersections as perceived by drivers, the following question can be applied:

“How safe is the service quality of signalized intersection $i$?”

To apply this method to transportation user perception, $x_{\delta}$ represents the degree of perception that transportation users have ranging from 0.0 to 1.0. This degree of perception is difficult to measure directly in the field. To reduce this difficulty, analysts can use an indicator or measure of effectiveness (MOE) of $x_{\delta}$ that provides an explanation of the association in the perception to be analyzed. For example, crash rate is a good indicator for the degree of highway safety as perceived by drivers. For the use of any indicator or MOE, the analyst should know the actual value of the indicators or MOE values in each case that participants state a degree of perception for. Previous studies indicated that this direct rating method results in fuzzy membership functions with a wider spread when compared to polling and pairwise comparison (Norwich and Turksen 1982 and Chameau and Santamarian 1987).

- **Reverse Rating**

The third method involves the use of a reverse rating technique and is called the “Vertical Method.” In this method, after specific degrees of membership are selected such as $u_{A}(\delta)=0, 0.5, 1.0$, a fuzzy membership degree, $u_{A}(\delta)$, is given to subjects. Then, they are asked to identify the corresponding subset of $x$ for which elements belonging to that degree correspond to the fuzzy value in question (Turksen 1988). Subjects are generally asked the following question:

Identify $\delta$ that has the degree $u_{A}(\delta)$
To apply this type of question in the evaluation of the service quality of signalized intersections as perceived by drivers, the following question can be applied:

“Identify the intersection that you have 0 percent agreement with that the service quality of this intersection is good.”

Chameau and Santamarian (1987) recommended this method as a valuable way to verify a fuzzy membership function already obtained through another approach rather than an acquisition method.

- **Interval estimation**

The fourth method involves the use of an interval estimation technique. The subject is asked to give an interval that describes the fuzzy value in question, \( x_\delta \). The following type of question is generally used for this experiment:

Give an interval in which degree you think the height of John lies \( u_A(\delta) \)

To apply this type of question in the evaluation of the service quality of signalized intersections as perceived by drivers, the following question can be applied:

“For what interval of waiting time do you consider a signalized intersection to have a fair condition?”

This method is more appropriate for situations where there is a clear linear ordering in the measurement of the fuzzy concept, as is the case when measuring height, heat, time, etc. (Dubois and Prade 2000). Chameau and Santamarian (1987) indicated that this method is a relatively simple way of acquiring the fuzzy membership function and it results in “less fuzzy” (the spread is narrower) membership functions when compared to the direct rating or polling methods.
- **Membership function exemplification**

The fifth method involves the use of a membership function exemplification technique, also called “continuous direct valuation.” This experimental method has been used in many studies due to its strength in producing more precise fuzzy membership functions (Kochen and Badre 1974, Hersh and Carmazza 1976, Zysno 1981, and Kulka and Novalc 1984). In this method, subjects are asked to rate the fuzzy values \( x_\delta \) or determine the degree of membership of \( x_\delta \) with respect to one of the fuzzy membership function descriptors. For example, analysts ask the subjects to determine the numerical values which are appropriate to represent vehicle speeds such as “low,” “medium,” “high,” and “very high.” Generally, the following question is used for this experimental method:

“To what degree \( \delta \) is \( A \)?”

To apply this type of question in the evaluation of the service quality of signalized intersections as perceived by drivers, the following question can be applied:

“To what degree does intersection \( i \) belong to the set of intersections having “good” service quality?”

However, directly applying this method to transportation user perception may be not appropriate. The results from this experimental method may show a great variance among the subjects’ responses. Also, subjects in this experiment are required to have some basic knowledge of fuzzy sets or be trained. This is because they have to answer in regards to the degree of membership that \( x \) is in the set “\( A \)” or not. Most of the participants for transportation studies have no knowledge of fuzzy sets, and they may have difficulty determining a certain degree of membership. Sancho and Verdegay (1999) indicated that this method requires knowledge of fuzzy sets by the experimental subject. For this reason, this method is more suitable when trained subjects can participate. However, use of trained subjects is not always applicable in the study of transportation systems.
**Pairwise Comparison**

The last method involves the use of pairwise comparisons. In this method, subjects are asked to select an object that best explains the fuzzy variable from among a pair of objects. Generally, the following question is used for this experimental method:

“Which is more $A$ (by how much)?”

To apply this type of question in the evaluation of the service quality of signalized intersections as perceived by drivers, the following question can be applied:

“Which intersection has better service quality, intersection 1 or intersection 2 (by how much)?”

There are several types of pairwise comparison methods used to measure a membership function, including binary comparison, absolute comparison, and Saaty’s pairwise comparison. Out these methods, Saaty’s pairwise comparison method is the one used most frequently. In Saaty’s pairwise comparison method, subjects are asked to show the degree of preference as well as the preferred object. This comparison is based on scaling ratios using the principal eigenvector of a positive pair-wise comparison matrix. Saaty developed the multiple criterion decision making process using a scaling method for priorities in hierarchical structures. The effect of the comparison scale was tested and nine scales or five scales were recommended. Through his tests, a comparison using nine scales produced better results than the others. He indicated that the wider scale increases the inconsistency of the answers of each subject, thereby producing a greater variation among subjects’ responses, which results in a wider the membership function. Through the nine linguistic comparison scales, the relative importance of each criterion to the other criterion is measured. The scales representing the relative importance of the criteria are expressed by the reciprocal matrix form, called the pair-wise comparison matrix (PCM) (Eq. 4.4).
where
\[ a_{ij} = \frac{w_i}{w_j} = \frac{1}{a_{ji}} \], for 1 ≤ i < n and 1 ≤ j < n (a_{ij} is a ratio of weights)

After the PCM is constructed, the weights are determined by finding a set of eigenvectors \( W = \{ w_1, w_2, w_3, w_4, w_5, w_6 \} \) corresponding to the largest eigenvalue that satisfies the following relationship (Eq. 4.5):

\[
(A - \lambda_{\text{max}} \cdot I) \cdot W = 0
\]

where
- \( W \) is the eigenvectors representing the weights of all the criteria considered, and
- \( \lambda_{\text{max}} \) is the largest eigenvalue of the matrix \( A \).

Using the normalized eigenvectors as weights generally ensures consistency and uniqueness (\( \sum w_i = 1 \)).

The pairwise comparison method can diminish one of the weaknesses of the polling and reverse rating methods by determining the membership function through a sequence of pairwise comparisons of the individual objects (Pedrycz and Gomide 1998). However, there are some difficulties in applying this method. The first difficulty is that a considerable number of comparisons are necessary. If the number of objects is large, the large number of questions for the pairwise comparison can frustrate the subjects. The greatest theoretical difficulty is the treatment of inconsistencies in the subject’s answers (Sancho and Verdegay 1999). However, it is a highly accurate method when determining the fuzzy weight of certain criteria, and it is the easiest method to apply to untrained
individuals who have no knowledge of fuzzy sets. For these reasons, the pairwise comparison method is an appropriate experimental method for the study of transportation user perception. Typically, it can be used in the construction of class 2 fuzzy membership functions even though it has some weaknesses in this application. To design simple questions and questions that are easy to answer is very important in the application of this method. Figure 4-5 shows an example of the question designed for use in this study.

1. **Length of waiting time vs. Length of gaps in traffic on the cross street**

   a. Please mark the one that you think is more important

   
   \[
   \begin{align*}
   \text{Length of waiting time} & \quad \underline{\phantom{00000}} \quad \\
   \text{Length of gaps in traffic on the cross street} & \quad \underline{\phantom{00000}}
   \end{align*}
   \]

   b. Then please circle a value on the scale below indicating the intensity of its importance (How much one is more important than other.)

   \[
   \text{Intensity of Importance}
   \]

   Scale (1-9): 1 2 3 4 5 6 7 8 9

   Definition: Equal Weak Strong Very Strong Absolute

   Figure 4-5: An Example Question Using Saaty’s Pairwise Comparison Method.

The selection of the most appropriate experimental method is very much dependent on the study types and participant types. For example, to investigate how drivers perceive the service quality of signalized intersection, membership function exemplification may not be suitable because the participating drivers are untrained and have no knowledge of fuzzy sets. The classes of fuzzy membership function influence the selection of the appropriate experimental method as well. For example, the pairwise comparison method is best for constructing fuzzy membership functions representing the relative importance of criteria, i.e., weight. There were several studies that compared these experimental methods to determine the more appropriate method (Chameau and
Santamarina 1987, Turksen 1991, Sancho and Verdegay 1999). Table 4-2 summarizes the strengths and weaknesses of the six experimental methods.
### Table 4-2: Strengths and Weakness of the Six Experimental Methods.

<table>
<thead>
<tr>
<th>Method</th>
<th>Strength</th>
<th>Weakness</th>
<th>Suitable Fuzzy Membership Function (FMF) Class</th>
</tr>
</thead>
</table>
| Polling                       | Easy and simple answering process                                       | Many questions need to be asked (L×N)                                                                                                  | • Class 1 FMFs  
|                               | Better method for layman                                                | Produces more subjective and dispersed responses which increase the fuzziness                                                        | • Class 3 FMFs  |
| Direct Rating                 | Simple answering process                                                | Minimum number of subjects is large ¹                                                                                                 | • Class 1 FMFs  
|                               | Better method for layman                                                |                                                                           | • Class 3 FMFs  |
| Reverse Rating                | Better method for experts                                               | Minimum number of subjects is small                                                                                                    | • Class 1 FMFs  
|                               | Minimum number of subjects is small                                      |                                                                           | • Class 3 FMFs  |
| Interval Estimation           | Simple answering process                                                |                                                                           | • Class 1 FMFs  |
|                               | More flexible response permits subjects to represent and estimate their  |                                                                           |                                                               |
|                               | conceptualization of the problem                                        |                                                                           |                                                               |
|                               | Less fuzziness (the spread of response is narrower) than direct rating   |                                                                           |                                                               |
|                               | or polling                                                              |                                                                           |                                                               |
| Membership Function Exemplification | No further processing needed                                           | More subjective and fuzzy answers                                                                                                      | • Class 1 FMFs  
|                               | Possible to verify the measurements by reverse rating                    | Better method for trained subjects or subjects who know fuzzy sets                                                                   | • Class 3 FMFs  |
|                               |                                                                           | Not applicable in the studies of transportation user perception                                                                    |                                                               |
| Pair-wise Comparison          | Easy to apply to untrained individuals                                   | More applicable for fuzzy membership function on a ratio scale                                                                       | • Class 2 FMFs  |
|                               | Construction of the FMF is more precise than other methods               | A considerable number of comparisons are necessary ($\frac{N^2 - N}{2}$)                                                                |                                                               |
|                               | Minimum number of subjects is small                                      | Less consistency in responses                                                                                                         |                                                               |

¹: Chameau and Santamarina (1999) recommended at least 15 subjects for direction rating method and at least 5 subjects for interval estimation.
The six experimental methods for the construction of fuzzy membership functions can be mixed and then applied based on the study characteristics. Figure 4-6 and 4-7 show examples where two different experimental methods are mixed to design survey questions. Figure 4-6 shows a question that is a mix of the “direct rating technique” and “membership exemplification,” and Figure 4-7 shows a question that is a mix of “interval estimation,” and “membership exemplification.”

**Please answer the following question regarding your perception of the overall service quality of this signalized intersection.**

1. What is your perception of the service quality at this intersection? (Please circle one of the linguistic values given below.)

   Poor  Acceptable  Good

2. What percentage of satisfaction do you get from this signalized intersection? (Please write your perception of this intersection’s service quality with numerical values ranging from 0 to 100. “0” means least satisfactory, and “100” means most satisfactory.)

**Figure 4-6: An Example of Questions Using the Direct Rating Method.**
One of the core procedures in the development of a fuzzy inference system is fuzzy rule
generation. The fuzzy rule is commonly generated through graphical fuzzy partitioning
and mapping using the functional relationship between input and output variables.
However, this simple graphical method of fuzzy rule generation is restricted if the input
variables are comprised of multiple factors. The number of fuzzy rules to be generated
with multiple factors grows exceedingly. In this chapter, a hierarchical fuzzy inference
system is described. This is one of the ways to overcome the problems of fuzzy rule
generation with multiple factors, and the most appropriate structure of the fuzzy inference
system for analyzing transportation user perception. Common fuzzy rule generation methods are introduced and a new method, using a fuzzy aggregation method, is proposed as well.

4.4.1 Determination of the Structure of a Fuzzy Inference System

As mentioned in the previous section, the decision of which variables to use for input and output in a fuzzy inference system is a very significant step in producing more reliable results. The determination of the structure of a fuzzy inference system is dependent on the selection of variables, typically the number of variables. To decide the number of variables to be used, two concepts in tradeoff relationship must be considered. They are “accuracy” and “interpretability.” Ishbuchi and Yamamoto (2003) introduced the idea of accuracy and interpretability and this tradeoff relationship in the development of a fuzzy inference system. They defined accuracy as the capability of the fuzzy model to express the behavior of the system in an understandable way. The interpretability is the capability of the fuzzy model to faithfully represent the modeled system. In terms of applying a fuzzy inference system to transportation, accuracy is the similarity between actual transportation users’ perceptions or behavior and the output from the developed fuzzy inference system. The accuracy and interpretability of the results from the fuzzy system is dependent on the model structure, the number of input variables, the number of fuzzy rules, the number of linguistic terms, and the shape of the fuzzy membership functions (Casillas et al. 2003).

Figure 4-8 explains the tradeoff relationship between accuracy and interpretability based on the number of antecedent variables and the generated fuzzy rules. Simple fuzzy systems with a small number of input variables have high interpretability and involve large errors. On the contrary, complicated fuzzy systems with many input variables have high accuracy but low interpretability.
Fuzzy inference systems have been applied in various applications. However, many studies have reported limitations of the conventional fuzzy inference system when dealing with multiple variables (Raju et al. 1991, Lee et al. 1995, Chen and Parng 1996, and Wang 1999). A conventional fuzzy inference system has a one level structure. The number of rules in a conventional fuzzy system increases exponentially with the number of variables and the number of descriptors for each fuzzy membership function involved. This is often termed the “rule explosion problem.” For example, if nine variables are used as criteria to evaluate service quality of urban streets (e.g., travel lane, access management, pedestrian/bicyclist facilities, traffic signal, volume/congestion, pavement quality, traffic sign, pavement marking, and Advanced Transportation Information System (ATIS) facilities), and each variable has three fuzzy membership function descriptors (e.g., poor, fair, and good), then the number of the fuzzy rules to be generated is $19683 (3^9 = 19683)$ using following equation (Eq. 4.6). It is extremely difficult to control such a large number of fuzzy rules in a fuzzy inference system.

Figure 4-8: Trade-off between Interpretability and Accuracy.
Note: This figure is an interpretation of figure 1 in the study of Ishbushi and Yamamoto (2003).
where

\[
\begin{align*}
R &= \text{the number of rules to be generated} \\
I_j &= \text{the number of linguistic descriptors for } j^{th} \text{ input variable} \\
n &= \text{the number of input variable}
\end{align*}
\]

Normally, three or four variables are the maximum number that can be considered as part of a conventional fuzzy inference system. The rule explosion problem is more complex when fuzzy logic is applied in the study of transportation user perception. This is because transportation user perception regarding transportation service or safety is usually affected by many factors, such as roadway geometry, traffic flows, driver characteristics, and other driving conditions. User perception may not be able to be determined by only a few factors. Also, each driving condition has many sub-elements. For example, geometric conditions consist of many measures: cross-section elements, horizontal and vertical alignment, and roadside environments. Previous studies emphasized multiple factors that should be considered in evaluation of transportation user perception. A survey-based study found that transportation users consider multiple factors to evaluate transportation service quality based on their own perception and each person may have a different aspect of the roadway environment in their own perception (Flannery et al. 2004). Another study emphasized a need for multidimensional factors to evaluate service quality based on travelers’ perception as follows (Flannery et al. 2005):

The results reinforce findings from previous research by demonstrating that drivers consider quality across several dimensions, including operations, safety and aesthetics. A comprehensive measure of quality from the perspective of the driver may require a multidimensional index that includes measures of travel efficiency, sense of safety, positive guidance and aesthetics.
There are several ways to solve the “rule-explosion problem” as shown in Table 4-3. A hierarchical fuzzy inference system, which is one with a hierarchical structure for the antecedent, is a more appropriate way to analyze transportation user perception. This is because factors influencing transportation user perception can be easily categorized and incorporated within a hierarchical structure. Additionally the hierarchical fuzzy inference system is relatively easy to apply when compared to other methods that have the mathematical complexity to be applied to transportation user perception.

<table>
<thead>
<tr>
<th>Method</th>
<th>Key Concept</th>
</tr>
</thead>
<tbody>
<tr>
<td>Roju, Zhou, and Kisner (1991)</td>
<td>Use of a hierarchical structure based on categorized input variables (multiple levels of a fuzzy inference system)</td>
</tr>
<tr>
<td>Yam (1997)</td>
<td>Use of rules having the greatest influence on the aggregated output of a fuzzy inference system</td>
</tr>
</tbody>
</table>

The hierarchical fuzzy system, proposed by Roju, Zhou, and Kisner (1991), can reduce the computational complexity of a multivariable fuzzy system and the number of rules. Figure 4-9 shows an example of a hierarchical fuzzy inference system that is comprised of (n-1) two-input fuzzy inference systems.
Construction of a hierarchical fuzzy inference system begins with a procedure for grouping input variables. Many different input variables are grouped based on their similarity, relationship, and attributes as a component of a group. In other words, the particular transportation user perception to be analyzed decomposes into its component attributes, each of which can be associated with a group. Then new variables are created to represent an overall impact or attribute of each group. These new variables are used as output variables in a lower level fuzzy inference system and input variables in an upper level fuzzy inference system. Through these groupings and creation of new variables, a hierarchical structure for fuzzy inference system is built. The highest level of the hierarchy is the overall user perception regarding a certain transportation system. The
next level indicates the component attributes for the overall transportation user perception. After a hierarchical structure is built, a fuzzy inference system for each level must be developed. Considering the previous service quality of urban streets example, the nine input variables can be grouped into three different attributes, such as a group including the components associated with geometric conditions, a group including the components associated with traffic operational condition, and a group including the components associated with the information system performance. For the geometric condition group, travel lane, access management, and pedestrian/bicyclist facilities can be its elements. For the traffic operational condition group, traffic signal, volume/congestion, turning lane can be its elements. The last group, information system performance, would include traffic signs, pavement marking, and ATIS facilities as its elements. The procedures for using a hierarchical fuzzy inference system will be illustrated through a median safety application described in chapter 6.

Figure 4-10 and Figure 4-11 show generic constructs for using a conventional fuzzy inference system and hierarchical fuzzy inference system. They also show how a hierarchical fuzzy inference system is more efficient for the study of transportation user perception in terms of the ability to reduce the number of fuzzy rules.
Conventional Fuzzy Inference System (if-then rule)

Travel Lane
- Poor
- Fair
- Good

Access Management
- Poor
- Fair
- Good

Pedestrian/Bicyclist Facilities
- Poor
- Fair
- Good

Traffic Signal
- Poor
- Fair
- Good

Volume/Congestion
- Poor
- Fair
- Good

Turning Lane
- Poor
- Fair
- Good

Traffic Sign
- Poor
- Fair
- Good

Pavement Marking
- Poor
- Fair
- Good

ATIS Facilities
- Poor
- Fair
- Good

Service Quality of Urban Streets
- Poor
- Fair
- Good

Total 19683 fuzzy rules should be generated ($3^3 = 19683$).

Figure 4-10: An Example of the Conventional Fuzzy Inference System.
27 fuzzy rules should be generated ($3^3=27$).

Figure 4-11: An Example of the Hierarchical Fuzzy Inference System.
4.4.2 Fuzzy Rule Generation

As mentioned previously, there are two methods used to generate fuzzy rules. The first method is to generate fuzzy rules using experts’ opinions based on their own knowledge and experience. This is called ‘fuzzy rule implication’ in certain explanations of fuzzy logic (Tsoukalas and Uhrig 1996, and Yen and Langari 1998). In this method, fuzzy rules are generated by a set of inference mechanisms between the input and the output variables that experts develop using their knowledge and experience. For example, Hamad and Kikuchi (2002) generated the fuzzy rules to explain a ‘congestion index’ using two input variables (i.e., travel speed rate and very low speed rate) based on the analysts’ instinctive judgment as shown in Table 4-4.

<table>
<thead>
<tr>
<th>Fuzzy Rules:</th>
<th>Travel Speed Rate (TSR)</th>
</tr>
</thead>
<tbody>
<tr>
<td>IF {**TSR is ________} and {VLSR is ________}, THEN (**Congestion Index is ________).</td>
<td>F</td>
</tr>
<tr>
<td><strong>Very Low Speed Rate (VLSR)</strong></td>
<td>High</td>
</tr>
<tr>
<td>Moderate</td>
<td>Very High</td>
</tr>
<tr>
<td>Low</td>
<td>High</td>
</tr>
</tbody>
</table>

These fuzzy rules were generated using knowledge and experience to develop the following notions: if travel speed rate is relatively high, and the very low speed rate is also relatively high, then transportation users perceive more severe congestion. On the contrary, if travel speed rate is relatively low and the very low speed rate is also relatively
low, then transportation users perceive a lower level of congestion. This fuzzy rule generation method is appropriate if there is no real data representing the output (consequent) variable of the fuzzy inference system, and if the functional relationship between input and output variable in the existing database is difficult to estimate due to a non-existent output (consequent) variable. However, the fuzzy rules generated by experts’ opinions can be different from the opinions held by users due to the different perception of the relative importance of each variable. A survey to compare transportation user perception by users and experts was conducted in this study and found that there was a statistically significant difference between relative importance of each variable perceived by users and the importance perceived by experts. Also the opinions of an expert group can be different from the opinions of other expert groups because the decision process is subjectively conducted based on their own knowledge and experience. Therefore, it is always not appropriate to generate fuzzy rules based on experts’ opinions when analyzing perceptions obtained from actual users of the transportation system. The experiment conducted to produce this comparative examination and its results will be explained later in section 4.5.

The second method is to generate fuzzy rules based on the functional relationship between input and output variables existing in a database. This is called “fuzzy rule mapping.” Conventionally, fuzzy rules are generated using two steps in this method: fuzzy partitioning and rule mapping. This method is commonly applied in fuzzy control applications because there are always two numerical variables (i.e., input and output variables) and a functional relationship between these two variables. If there are a small number of input variables (i.e., antecedents) and the functional relationships are not complicated, fuzzy partitioning and rule mapping can be conducted manually using a graphical partition as shown in Figure 4-12.
However, if there are a large number of input variables or the functional relationship between the variables is complicated, manual fuzzy partitioning and fuzzy rule mapping are restricted. In these cases, other intelligent techniques (i.e., artificial neural network and genetic algorithm) can be applied to generate fuzzy rules more appropriately. This method is called an “advanced fuzzy inference system” or a “hybrid fuzzy inference system.” In these hybrid methods of fuzzy rule generation, the complicated functional relationship between the variables is identified by the above mentioned techniques, and then fuzzy rules are mapped through the functional relationship and partition. This type of hybrid fuzzy inference system has been applied to many complicated problems (Masuoka et al. 1990, Jang 1993, Shieh et al. 1999, and Li et al. 2004). These fuzzy rule mapping methods, including the manual and hybrid methods, can be conducted only if there are true output values and a functional relationship between the input and output variables. However, when dealing with transportation user perception, since each user’s perception is unique, generally a “true” perception as an output variable does not exist. For example, when drivers evaluate the degree of congestion on a roadway, each person may have a different perception of the degree of congestion. Even though they evaluate the same roadway, the degree of congestion perceived by a driver may be different from the degree of congestion perceived by
another driver due to differences in their personalities. Further, even though the same
driver evaluates the roadway, the degree of congestion perceived by the driver can be
different according to the situation the driver is in. For example, a 10 minute delay
caused by congestion when the driver is going to work is different from that when the
driver is going home. This is because the trip to work is more time-sensitive than the trip
home (for some drivers, at least). Figure 4-13 shows an example of the structure of the
hybrid fuzzy inference system using an artificial neural network technique.

Figure 4-13: Hybrid Fuzzy Inference System Using Artificial Neural Network.
Source: Jang, J.R., ANFIS: Adaptive-Network-Based Fuzzy Inference System
To overcome the weakness of the existing fuzzy rule generation methods mentioned above, a new method using a fuzzy aggregation technique is proposed in this study. The fuzzy aggregation method that was introduced in the previous section, section 4.2.1, is a way to estimate overall perception while taking into consideration the relatively different importance of each input variable. Using this overall perception aggregated by the fuzzy weighted average, partitions to generate fuzzy rules can be conducted even though there are large numbers of input variables in an existing database, no output value, or no functional relationship between input and output variables. When dealing with transportation user perception, there is usually no true value, which is used as an output variable for mapping the fuzzy rules in the fuzzy inference system. The defuzzified fuzzy weighted average can be used as a true value (i.e., output value) to find a functional relationship in the fuzzy partitioning and rule mapping step. The process to calculate the fuzzy weighted average was already explained in a previous section, 4.2, and the application of the proposed method will be described in chapter 6 using a median safety application.

After conducting fuzzy aggregation, each aggregated fuzzy value is defuzzified using the selected defuzzification method. These defuzzified values are plotted, and then graphically partitioned with the determined number of fuzzy membership descriptors for the output variable. Based on this graphical partition, the fuzzy rules can be mapped. Table 4-5 shows the strengths and weaknesses of the three methods. Figure 4-14 shows the entire procedure of the proposed fuzzy rule generation method.
<table>
<thead>
<tr>
<th>Methods</th>
<th>Strengths</th>
<th>Weaknesses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fuzzy Rule Implication</td>
<td>• Applicable without functional relationships between input and output variables in an existing database</td>
<td>• The fuzzy rules generated subjectively by experts can be different from those by users or by other expert groups • Restricted for large number of input variables or complicated problems</td>
</tr>
<tr>
<td>Fuzzy Rule Mapping (manual)</td>
<td>• Ability to generate more objective and accurate fuzzy rules corresponding to the relationship between input and output variables • Easy and simple</td>
<td>• Applicable only if there are true output values (i.e., subjective transportation user perception) and functional relationships between input and output variables in an existing database (There is usually no true output values for use perception problems) • Not applicable for large numbers of input variables or complicated problems</td>
</tr>
<tr>
<td>Hybrid Fuzzy Rule Mapping</td>
<td>• Ability to generate more objective and accurate fuzzy rules corresponding to the relationship between real input and output data • Applicable for complicated problems</td>
<td>• Applicable only if there are true output values (i.e., subjective transportation user perception) in an existing database • Relatively complex procedures and difficult to apply</td>
</tr>
<tr>
<td>Proposed Fuzzy Rule Generation</td>
<td>• Fuzzy rules generated based on perception of actual transportation users • Applicable without a true output value and functional relationship between input and output variables in an existing database • Applicable for a large number of input variables or complicated problems</td>
<td>• Need to construct fuzzy weights for each input variable based on surveys of transportation users</td>
</tr>
</tbody>
</table>
Figure 4-14: The Procedures of the Proposed Fuzzy Rule Generation Method Using Fuzzy Aggregation Technique.
4.5 Comparison of User Perception of Public Users and Experts

4.5.1 Introduction

Transportation user perception was mainly obtained through surveys or experiments with laymen or experts. Transportation user perception was often assessed indirectly through analyses of driver behaviors such as speed, speed changing rates, or headway. However, through these indirect ways, it is difficult to truly analyze how transportation users perceive the quality of particular transportation systems. For the most part, prior studies were conducted using experts as subjects instead of the general public. There seems to be an underlying advantage in having experts complete the surveys rather than using members of the public. Experts usually understand, more fully, the questions that the analysts ask and their responses are often more precisely than system users. In many of these studies, it was supposed that the results of surveys with a small number of experts were able to represent the general opinions of users, which should be collected from a large subject pool, in certain types of studies.

In studies using fuzzy approaches, surveys employing experts are more commonly used to construct fuzzy membership functions rather than surveys with respondents from the public (Loizos 2001). However, there is a significant issue in conducting surveys using a small number of experts rather than a large number of public people. The issue is whether the experts’ opinions truly represent the users’ perceptions or not. In other words, are the experts’ opinions different from the public’s opinions?

To investigate the difference, surveys were completed by both a public user group and an expert group with the same questions. These questions were used to construct the fuzzy membership functions relative to the application for variable message signs (VMS). The complete procedures and results of the VMS fuzzy application will be explained in the chapter 5.
4.5.2 Method

4.5.2.1 Survey

The surveys of public user perception were conducted in six classes during the 2004 summer and fall semesters at the Pennsylvania State University. Meanwhile, the surveys of expert perception were conducted at two different meetings where a number of transportation experts were in attendance, the 2004 Transportation Research Board Highway Capacity and Quality of Service Committee Midyear Meeting and Conference and the 10th Transportation Engineering and Safety Conference. The 2004 Highway Capacity and Quality of Service Committee Midyear Meeting and Conference and the 10th Transportation Engineering and Safety Conference (TESC Conference) were held in State College Pennsylvania from July 21 to 24, 2004 and December 8 to 10, 2004, respectively. Table 4-6 shows the samples sizes for each group. Out of those numbers of respondents, some incomplete and strange responses were excluded from the comparisons.

<table>
<thead>
<tr>
<th>Group</th>
<th>Public</th>
<th>Expert</th>
</tr>
</thead>
<tbody>
<tr>
<td>6 PSU Classes</td>
<td>64</td>
<td>74</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>16</td>
</tr>
<tr>
<td>HCM committee</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TESC Conference</td>
<td></td>
<td>58</td>
</tr>
</tbody>
</table>

The survey questionnaires consisted of two parts, and the results of each part were used to construct different types of fuzzy membership function. The first part was designed to investigate how people form their perception by having them state their level of agreement or disagreement with some direct statement about the service quality of variable message signs (VMS) elements according to a 5-point scale: strongly unsatisfactory, unsatisfactory, neither unsatisfactory nor satisfactory, satisfactory, and
strongly satisfactory. To represent their perceptions as a fuzzy membership function, the interval estimation method was used. Interval estimation is known as the method that can generate more suitable results for continuous measurements. Participants understand and represent their opinions more easily using interval estimation. Also membership functions constructed using interval estimation are more precise as compared to those developed using direct rating or polling methods. From the responses from this part of the survey, a type of fuzzy membership function for comparison was constructed. This type of fuzzy membership function represents how people form their perception using qualitative variables, such as agreement or satisfaction. Figure 4-15 shows the questions used to create the first type of fuzzy membership function in the comparison.

Please answer the following questions to classify the five “agreement/disagreement” levels you would have used in answering the survey using a scale from 0% to 100%.

Example
“\textit{I will answer in ‘\textbf{Strongly Disagree}’ when my agreement ranges from 0\% to 10\%.”}

a. I will answer in ‘\textbf{Strongly Disagree}’ when my agreement ranges from ______% to ______%.

b. I will answer in ‘\textbf{Disagree}’ when my agreement ranges from ______% to ______%.

c. I will answer in ‘\textit{Neither Agree nor Disagree}’ when my agreement ranges from ______% to ______%.

d. I will answer in ‘\textbf{Agree}’ when my agreement ranges from ______% to ______%.

e. I will answer in ‘\textbf{Strongly Agree}’ when my agreement ranges from ______% to ______%.

Figure 4-15: Questions Used to Create the First Type of Fuzzy Membership Function Used in the Comparison.
The second part of the questionnaires investigated the importance of different criteria used to evaluate VMS service quality including visibility, legibility to read, comprehension of message displayed, accuracy of information, usefulness of information, and correspondence between information displayed and expected by drivers. To obtain the relative importance of the criteria, the questions were designed using Saaty’s pair-wise comparison. Generally, the pair-wise comparison method is known to produce significantly more precise results (Juang et al. 1992). Saaty’s pair-wise comparison method is a means to assess the weights of the criteria using the principal eigenvector of a positive pair-wise comparison matrix. In this method, the relative importance of each criterion to the other criteria is measure through certain levels of the linguistic comparison scales. From these results, another type of fuzzy membership function was constructed. This second type of fuzzy membership function represents the relative importance of those VMS service quality criteria. Figure 4-16 shows an example of the questions used for this second comparison. All questions used in the experiment are included in Appendix A.
4.5.2.2 Statistic Comparison

The comparisons of the public and experts’ opinions were conducted by an independent sample t-test. The independent sample t-test is a hypothesis test for answering questions about the mean when the data are collected from two different samples of independent observations and the data are normally distributed. To conduct the independent sample t-test, three assumptions should be met as follows:

1. The dependent variable is normally distributed.
2. The two groups have approximately equal variance on the dependent variable.
3. The two groups are independent of one another.

The sampling of each group’s opinion was conducted totally independently using different participants at different locations at different times as mentioned above. The

\[
\begin{array}{|c|c|c|c|c|c|c|c|c|}
\hline
\text{Visibility vs. Legibility to read} \\
\hline
\text{Intensity of Importance} \\
\hline
\text{Scale (1-9)} & 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 \\
\hline
\text{Definition} & \text{Equal} & \text{Weak} & \text{Strong} & \text{Very Strong} & \text{Absolute} \\
\hline
\end{array}
\]

Please write a number on one line of the pair-wise comparison according to the relative importance of one factor over the other using above scales.

‘Visibility’ over ‘Legibility to read’ with ________ intensity

OR

‘Legibility to read’ over ‘Visibility’ with ________ intensity

Figure 4-16: An Example of the Questions Used for the Second Comparison.
sample size for each group was large enough to conclude that the variables were approximately normally distributed using the Central Limit Theorem. Since the variables of each group were normally distributed, it was also concluded that the variation of the mean difference between the two groups followed a normal distribution. To test the equal variance on the dependent variables, the Levene’s Test was conducted. If the assumption of equal variance is valid, the following test statistic is used (Eq. 4.7):

$$t^* = \frac{x_A - x_B}{\sqrt{\frac{v_p}{n_A} + \frac{v_p}{n_B}}}$$

Eq. 4.7

$$df = n_A + n_B - 2$$

where

$$v_p = \frac{(n_A - 1)v_A + (n_B - 1)v_B}{n_A + n_B - 2}$$

$$t^* = \text{pooled } t\text{-statistics}$$

$$v_p = \text{the pooled variance computed}$$

If the assumption of equal variance is not valid, the following test statistic is used (Eq. 4.8):

$$t^{**} = \frac{x_A - x_B}{\sqrt{\frac{s_A^2}{n_A} + \frac{s_B^2}{n_B}}}$$

Eq. 4.8

$$df = \frac{(s_A^2 / n_A + s_B^2 / n_B)}{(s_A^2 / n_A)^2 / n_A + (s_B^2 / n_B)^2 / n_B}$$

where

$$t^{**} = \text{separated } t\text{-statistics}$$

$$s_A^2, s_B^2 = \text{sample variance of public group and expert group, respectively}.$$
Since the survey results from the first part consisted of interval values, the results can be described with two variables, the middle value of the interval and the length of the interval. Also, these two variables critically influence the shape of the constructed fuzzy membership functions. Under these circumstances, an independent sample t-test for each variable was conducted separately. The null hypothesis for the first variable is that there is no difference between the middle value of the intervals defined by the public and those defined by the experts. Another null hypothesis is that there is no difference between the length of the interval estimated by the public and the one estimated by the experts.

The analysis of the second set of survey questions consisted of 15 pair-wise comparisons with the intensity of importance, and the results were formed by matrix formation. For this reason, the responses from two groups were difficult to compare directly. Due to this difficulty, the weights of each criterion, calculated though Saaty’s pair-wise comparison method, were used to investigate the difference between the public and the experts responses instead of using the raw data from the second survey.

4.5.3 Results

4.5.3.1 Comparison of Decision Making Thresholds for Five-Point Scale.

As mentioned above, two variables, the middle value and the length of the interval, were compared. Table 4-7 and Table 4-8 show a summary of the descriptive statistics for the two variables for each interval from the survey. As shown in these tables, statistics of the middle values and the lengths of the intervals of the two groups are very similar.
Table 4-7: Summary of Descriptive Statistics for the Middle Value of Each Interval.

<table>
<thead>
<tr>
<th>Scale</th>
<th>Group</th>
<th>Number of sample</th>
<th>Mean</th>
<th>Std. Deviation</th>
<th>Min.</th>
<th>Max</th>
<th>Std. Error Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strongly disagree</td>
<td>Public</td>
<td>55</td>
<td>8.182</td>
<td>3.583</td>
<td>2.5</td>
<td>20.0</td>
<td>0.483</td>
</tr>
<tr>
<td></td>
<td>Expert</td>
<td>65</td>
<td>7.619</td>
<td>3.447</td>
<td>0.5</td>
<td>20.0</td>
<td>0.428</td>
</tr>
<tr>
<td>Disagree</td>
<td>Public</td>
<td>55</td>
<td>27.591</td>
<td>6.579</td>
<td>12.5</td>
<td>45.0</td>
<td>0.887</td>
</tr>
<tr>
<td></td>
<td>Expert</td>
<td>65</td>
<td>28.000</td>
<td>5.878</td>
<td>10.0</td>
<td>45.0</td>
<td>0.729</td>
</tr>
<tr>
<td>Neither agree nor disagree</td>
<td>Public</td>
<td>55</td>
<td>49.463</td>
<td>5.626</td>
<td>30.0</td>
<td>75.0</td>
<td>0.759</td>
</tr>
<tr>
<td></td>
<td>Expert</td>
<td>65</td>
<td>50.035</td>
<td>4.865</td>
<td>28.8</td>
<td>62.5</td>
<td>0.603</td>
</tr>
<tr>
<td>Agree</td>
<td>Public</td>
<td>55</td>
<td>72.146</td>
<td>5.298</td>
<td>62.5</td>
<td>90.0</td>
<td>0.714</td>
</tr>
<tr>
<td></td>
<td>Expert</td>
<td>65</td>
<td>72.246</td>
<td>5.586</td>
<td>47.5</td>
<td>85.0</td>
<td>0.693</td>
</tr>
<tr>
<td>Strongly agree</td>
<td>Public</td>
<td>55</td>
<td>92.091</td>
<td>3.219</td>
<td>85.0</td>
<td>97.5</td>
<td>0.434</td>
</tr>
<tr>
<td></td>
<td>Expert</td>
<td>65</td>
<td>92.400</td>
<td>3.515</td>
<td>80.0</td>
<td>99.5</td>
<td>0.436</td>
</tr>
</tbody>
</table>

Table 4-8: Summary of Descriptive Statistics for the Length of Interval of Each Interval.

<table>
<thead>
<tr>
<th>Scale</th>
<th>Group</th>
<th>Number of sample</th>
<th>Mean</th>
<th>Std. Deviation</th>
<th>Min.</th>
<th>Max</th>
<th>Std. Error Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strongly disagree</td>
<td>Public</td>
<td>55</td>
<td>16.364</td>
<td>7.166</td>
<td>5.0</td>
<td>40.0</td>
<td>0.966</td>
</tr>
<tr>
<td></td>
<td>Expert</td>
<td>65</td>
<td>15.239</td>
<td>6.895</td>
<td>1.0</td>
<td>40.0</td>
<td>0.855</td>
</tr>
<tr>
<td>Disagree</td>
<td>Public</td>
<td>55</td>
<td>22.455</td>
<td>7.810</td>
<td>5.0</td>
<td>40.0</td>
<td>1.053</td>
</tr>
<tr>
<td></td>
<td>Expert</td>
<td>65</td>
<td>24.600</td>
<td>8.452</td>
<td>5.0</td>
<td>47.0</td>
<td>1.048</td>
</tr>
<tr>
<td>Neither agree nor disagree</td>
<td>Public</td>
<td>55</td>
<td>21.291</td>
<td>9.708</td>
<td>10.0</td>
<td>50.0</td>
<td>1.309</td>
</tr>
<tr>
<td></td>
<td>Expert</td>
<td>65</td>
<td>19.180</td>
<td>9.105</td>
<td>0.0</td>
<td>40.0</td>
<td>1.129</td>
</tr>
<tr>
<td>Agree</td>
<td>Public</td>
<td>55</td>
<td>24.073</td>
<td>7.750</td>
<td>10.0</td>
<td>45.0</td>
<td>1.045</td>
</tr>
<tr>
<td></td>
<td>Expert</td>
<td>65</td>
<td>25.262</td>
<td>6.520</td>
<td>15.0</td>
<td>48.0</td>
<td>0.809</td>
</tr>
<tr>
<td>Strongly agree</td>
<td>Public</td>
<td>55</td>
<td>15.818</td>
<td>6.438</td>
<td>5.0</td>
<td>30.0</td>
<td>0.868</td>
</tr>
<tr>
<td></td>
<td>Expert</td>
<td>65</td>
<td>15.200</td>
<td>7.029</td>
<td>1.0</td>
<td>40.0</td>
<td>0.872</td>
</tr>
</tbody>
</table>

Table 4-9 shows the results of Levene’s Test for equality of variances. In all cases, for both the middle value and the length of interval, the observed significance was relatively high. Therefore, it was concluded that two groups had equal variance and pooled
statistics should be used to compare the decision making thresholds or trends for five-point scales from the public and expert users.

As shown in Table 4-10 and Table 4-11, all t-statistics are significantly further from the rejection region at the five percent significance level, and all p-values for independent sample t-test are significantly high. From these test results, the null hypothesis that the means of the middle values between public opinion and expert opinion are equal failed to be rejected. The null hypothesis for the length of intervals also failed to be rejected. Therefore, it can be concluded that the mean and variance of both the middle value of the intervals and the length of the intervals for all five levels of agreement or disagreement are not statistically different at the five percent significance level (α=0.05). In other words, decision making thresholds or trends of both public users and experts are not statistically different at the five percent significance level when responding to a 5-point scale survey regarding perception of agreement and disagreement.

Table 4-9: Results of Levene’s Test for Equality of Variances.

<table>
<thead>
<tr>
<th>Scale</th>
<th>Middle value</th>
<th>Length of interval</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>F</td>
<td>P</td>
</tr>
<tr>
<td>Strongly disagree</td>
<td>0.044</td>
<td>0.834</td>
</tr>
<tr>
<td>Disagree</td>
<td>1.143</td>
<td>0.287</td>
</tr>
<tr>
<td>Neither agree nor disagree</td>
<td>0.724</td>
<td>0.397</td>
</tr>
<tr>
<td>Agree</td>
<td>0.152</td>
<td>0.698</td>
</tr>
<tr>
<td>Strongly agree</td>
<td>0.000</td>
<td>0.991</td>
</tr>
</tbody>
</table>
This finding indicates that a survey using experts instead of users to construct fuzzy membership functions that represent how people form their perceptions using certain levels of qualitative variables, such as agreement or satisfaction, can be conducted and produce similar results. However, it is important to note that this lack of a difference between the public’s and the experts’ perception relates only to their decision making thresholds or trends on a five-point scale, not about their perception regarding service.

### Table 4-10: Independent Sample Test Results for the Means of the Middle Values of Each Interval.

<table>
<thead>
<tr>
<th>Scale</th>
<th>T</th>
<th>d.f.</th>
<th>P</th>
<th>Mean difference</th>
<th>Std. Error Difference</th>
<th>95% C.I.</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Strongly disagree</td>
<td>0.875</td>
<td>118</td>
<td>0.383</td>
<td>0.563</td>
<td>0.643</td>
<td>-0.711</td>
<td>1.836</td>
<td></td>
</tr>
<tr>
<td>Disagree</td>
<td>-0.360</td>
<td>118</td>
<td>0.720</td>
<td>-0.409</td>
<td>1.137</td>
<td>-2.662</td>
<td>1.843</td>
<td></td>
</tr>
<tr>
<td>Neither agree nor disagree</td>
<td>-0.596</td>
<td>118</td>
<td>0.552</td>
<td>-0.571</td>
<td>0.958</td>
<td>-2.467</td>
<td>1.325</td>
<td></td>
</tr>
<tr>
<td>Agree</td>
<td>-0.101</td>
<td>118</td>
<td>0.920</td>
<td>-0.101</td>
<td>1.000</td>
<td>-2.080</td>
<td>1.879</td>
<td></td>
</tr>
<tr>
<td>Strongly agree</td>
<td>-0.499</td>
<td>118</td>
<td>0.619</td>
<td>-0.309</td>
<td>0.620</td>
<td>-1.536</td>
<td>0.918</td>
<td></td>
</tr>
</tbody>
</table>

### Table 4-11: Independent Sample Test Results for the Length of Interval of Each Interval.

<table>
<thead>
<tr>
<th>Scale</th>
<th>t</th>
<th>d.f.</th>
<th>P</th>
<th>Mean difference</th>
<th>Std. Error Difference</th>
<th>95% C.I.</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Strongly disagree</td>
<td>0.875</td>
<td>118</td>
<td>0.383</td>
<td>1.125</td>
<td>1.286</td>
<td>-1.422</td>
<td>3.672</td>
<td></td>
</tr>
<tr>
<td>Disagree</td>
<td>-1.434</td>
<td>118</td>
<td>0.154</td>
<td>-2.145</td>
<td>1.496</td>
<td>-5.108</td>
<td>0.817</td>
<td></td>
</tr>
<tr>
<td>Neither agree nor disagree</td>
<td>1.229</td>
<td>118</td>
<td>0.221</td>
<td>2.114</td>
<td>1.720</td>
<td>-1.291</td>
<td>5.519</td>
<td></td>
</tr>
<tr>
<td>Agree</td>
<td>-0.913</td>
<td>118</td>
<td>0.363</td>
<td>-1.189</td>
<td>1.303</td>
<td>-3.768</td>
<td>1.391</td>
<td></td>
</tr>
<tr>
<td>Strongly agree</td>
<td>0.499</td>
<td>118</td>
<td>0.619</td>
<td>0.618</td>
<td>1.239</td>
<td>-1.836</td>
<td>3.073</td>
<td></td>
</tr>
</tbody>
</table>
quality of certain transportation facilities. In other words, experts can respond differently regarding the service quality of certain transportation facilities from users but their thresholds in selecting levels of agreement or satisfaction among five levels are not statistically different.

4.5.3.2 Comparison of Relative Importance of Each Criterion Determined by Public Users and Experts

As mentioned above, the comparison of relative importance of each criterion determined by users and experts was conducted using the normalized weights of each criterion calculated though Saaty’ pair-wise comparison method. The weight values ranged 0 to 1, and the total sum of the weights for six criteria was 1. Lower values mean lower importance for the six criteria, and higher values mean higher importance. Table 4-12 shows the summary of descriptive statistics for the weights among the six criteria calculated. As shown in these tables, the means and standard deviations for visibility and correspondence of the users are very similar to the means and standard deviations of the experts. Those for other criteria are different. The order of the weight of the six criteria based on the mean of weight for each criterion is also different. The results show that the order of relative importance for users was: accuracy, usefulness, comprehension, legibility, visibility, and correspondence. However, the order for the experts was: comprehension, accuracy, legibility, usefulness, visibility, and correspondence.
Table 4-13 shows the results of Levene’s Test for equality of variances. In the cases of
legibility and accuracy, the observed p-value is less than the given significance level
(\( \alpha = 0.05 \)). P-values for other criteria, visibility, comprehension, usefulness and
correspondence, are large enough to conclude that two groups had equal variance.
Therefore, it was concluded that two groups for legibility and accuracy had statistically
unequal variance, and two groups for the other four criteria had equal variance. Based on
the results of Levene’s Test, pooled statistics for visibility, comprehension, usefulness
and correspondence and separated statistics for legibility and accuracy were used to
compare the relative importance of each criterion determined by the users and experts.

Table 4-13: Levene’s Test for Equality of Variances for the Second Comparison.

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Weights of Each Criterion</th>
<th>F</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Visibility</td>
<td></td>
<td>0.015</td>
<td>0.904</td>
</tr>
<tr>
<td>Legibility</td>
<td></td>
<td>5.473</td>
<td>0.021</td>
</tr>
<tr>
<td>Comprehension</td>
<td></td>
<td>2.723</td>
<td>0.102</td>
</tr>
<tr>
<td>Accuracy</td>
<td></td>
<td>4.835</td>
<td>0.030</td>
</tr>
<tr>
<td>Usefulness</td>
<td></td>
<td>0.934</td>
<td>0.336</td>
</tr>
<tr>
<td>Correspondence</td>
<td></td>
<td>2.448</td>
<td>0.120</td>
</tr>
</tbody>
</table>
As shown in Table 4-14, the p-values for legibility, comprehension, and accuracy are smaller than 0.05, which is the given level of significance. However, the p-values for visibility, usefulness, and correspondence are larger than the significance level. From these test results, the null hypotheses for legibility, comprehension, and accuracy that the mean of the relative importance of these three criteria is equal were rejected at the five percent level of significance but those for visibility, usefulness, and correspondence failed to be rejected. Even at the 0.06 p-value no statistically significant difference is indicated at the five percent significance level; 0.06 is a relatively small value and the null hypothesis can be rejected at a higher significance level, for example $\alpha = 0.1$.

Therefore, there is not sufficient evidence that the weight from users and experts are not different. Table 4-15 summarizes the statistical test regarding the relative importance of the evaluation criteria.

<table>
<thead>
<tr>
<th>Criteria</th>
<th>t</th>
<th>d.f.</th>
<th>p</th>
<th>Mean Difference</th>
<th>Std. Error Difference</th>
<th>95% C.I.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Visibility</td>
<td>0.100</td>
<td>114.0</td>
<td>0.920</td>
<td>-0.002</td>
<td>0.022</td>
<td>-0.041 to 0.045</td>
</tr>
<tr>
<td>Legibility*</td>
<td>-2.716</td>
<td>113.3</td>
<td>0.008</td>
<td>-0.054</td>
<td>0.020</td>
<td>-0.093 to -0.015</td>
</tr>
<tr>
<td>Comprehension</td>
<td>-3.005</td>
<td>114.0</td>
<td>0.003</td>
<td>-0.058</td>
<td>0.019</td>
<td>-0.096 to -0.020</td>
</tr>
<tr>
<td>Accuracy*</td>
<td>2.147</td>
<td>98.8</td>
<td>0.034</td>
<td>0.053</td>
<td>0.025</td>
<td>0.004 to 0.102</td>
</tr>
<tr>
<td>Usefulness</td>
<td>1.900</td>
<td>114.0</td>
<td>0.060</td>
<td>0.040</td>
<td>0.021</td>
<td>-0.002 to 0.081</td>
</tr>
<tr>
<td>Correspondence</td>
<td>1.139</td>
<td>114.0</td>
<td>0.257</td>
<td>0.017</td>
<td>0.015</td>
<td>-0.012 to 0.046</td>
</tr>
</tbody>
</table>

*: This criterion was found at the criterion having different variance, and the separated statistics are shown in the table.
4.5.3.3 Comparison of the Constructed Fuzzy Membership Functions

The first comparison was for fuzzy membership functions representing the decision making thresholds for the five-point scale of linguistic statements. These fuzzy membership functions were constructed through a review of the responses. The shapes of the histograms derived from these normalized frequencies of the responses indicated that a trapezoid membership function was the most appropriate type of membership function for representing five scales of linguistic statements. The trapezoidal membership function is specified by four parameters \( \{a, b, c, d\} \) as mentioned in Table 2-2:

\[
\text{trapezoid } f(x; a, b, c, d) = \begin{cases} 
0 & x \leq a \\
\frac{x - a}{b - a} & a \leq x \leq b \\
\frac{1}{b - c} & b \leq x \leq c \\
\frac{d - x}{d - c} & c \leq x \leq d \\
0 & d \leq x 
\end{cases}
\]

The parameters for fuzzy membership function based on the responses from the users are same as those from the experts. Table 4-16 shows the four parameters, and Figure 4-17 shows the fuzzy membership functions for the decision making thresholds for the five-point scale of linguistic statements.
The second comparison was for fuzzy membership functions representing the relative importance, weight, of each criterion determined by users and experts. The weights of each criterion evaluated by Saaty’s eigenvector method based on the responses from the users and experts were used to construct the fuzzy weights of each criterion. Review of the data indicated that triangular fuzzy membership functions were the most suitable type.

Table 4-16: Parameters of Fuzzy Membership Functions for the Decision Making Thresholds for the Five-point Scale.

<table>
<thead>
<tr>
<th>Scale</th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (Strongly Disagree)</td>
<td>-</td>
<td>0</td>
<td>0.100</td>
<td>0.200</td>
</tr>
<tr>
<td>2 (Disagree)</td>
<td>0.100</td>
<td>0.200</td>
<td>0.300</td>
<td>0.450</td>
</tr>
<tr>
<td>3 (Neither agree nor disagree)</td>
<td>0.300</td>
<td>0.450</td>
<td>0.500</td>
<td>0.650</td>
</tr>
<tr>
<td>4 (Agree)</td>
<td>0.500</td>
<td>0.650</td>
<td>0.725</td>
<td>0.925</td>
</tr>
<tr>
<td>5 (Strongly Agree)</td>
<td>0.725</td>
<td>0.925</td>
<td>1</td>
<td>-</td>
</tr>
</tbody>
</table>

Figure 4-17: Fuzzy Membership Functions for the Decision Making Thresholds for the Five-point Scale.
of membership function for representing the weights of the six criteria. A triangular membership function is specified by three parameters \(\{a, b, c\}\), and the precise appearance of the function is determined by the choice of parameters as mentioned in Table 2-2:

\[
\text{triangle } f(x; a, b, c) = \begin{cases} 
0 & x \leq a \\
\frac{x-a}{b-a} & a \leq x \leq b \\
\frac{c-x}{c-b} & b \leq x \leq c \\
0 & c \leq x 
\end{cases}
\]

These three parameters were finally determined through a review of the histograms and the basic statistic descriptors, such as minimum, mode, median, mean, and maximum values. Table 4-17 shows the three parameters, and Figure 4-18 show the fuzzy weights based on the responses of the users and experts. Through a general review of those fuzzy weights, it was found that the fuzzy weights of legibility and comprehension based on the experts’ responses were higher than those based on the users’ responses. On the contrary, the fuzzy weights of accuracy and usefulness based on the experts’ responses were lower than those based on the users’ responses. The fuzzy weights of visibility and correspondence from both the experts and users were relatively similar. Those results are similar to the previous results of the statistical tests. As shown in Table 4-17 and Figure 4-18, the experts estimated that the comprehension of a message displayed through VMS is the most important criterion to evaluate the service quality of VMS, but the users estimated that the accuracy of the information is the most important criterion.
<table>
<thead>
<tr>
<th>Criteria</th>
<th>Expert</th>
<th>Public</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>a</td>
<td>b</td>
</tr>
<tr>
<td>Visibility</td>
<td>0.018</td>
<td>0.098</td>
</tr>
<tr>
<td>Legibility</td>
<td>0.023</td>
<td>0.170</td>
</tr>
<tr>
<td>Comprehension</td>
<td>0.033</td>
<td>0.220</td>
</tr>
<tr>
<td>Accuracy</td>
<td>0.026</td>
<td>0.179</td>
</tr>
<tr>
<td>Usefulness</td>
<td>0.022</td>
<td>0.126</td>
</tr>
<tr>
<td>Correspondence</td>
<td>0.015</td>
<td>0.080</td>
</tr>
</tbody>
</table>

Table 4-17: Parameters of Fuzzy Weights of Each Criterion.
a) Fuzzy Weight of Visibility

b) Fuzzy Weight of Legibility

Figure 4-18: Fuzzy Weights for the Six Criteria.
c) Fuzzy Weight of Comprehension

![Graph showing fuzzy weights for comprehension](image)

d) Fuzzy Weight of Accuracy

![Graph showing fuzzy weights for accuracy](image)

Figure 4-18: Fuzzy Weights for the Six Criteria (con’t).
e) Fuzzy Weight of Usefulness

![Graph showing fuzzy weights for usefulness]

f) Fuzzy Weight of Correspondence

![Graph showing fuzzy weights for correspondence]

Figure 4-18: Fuzzy Weights for the Six Criteria (con’t).
CHAPTER 5
USE OF FUZZY SETS TO EVALUATE DRIVER PERCEPTION OF SERVICE QUALITY OF VARIABLE MESSAGE SIGNS

5.1 Introduction

Advanced traveler information systems (ATIS) are an intelligent transportation sub-area that has significant interactions between the systems and humans, whether they are vehicle operators, passengers, or pedestrians. Given this circumstance, consideration of how drivers perceive and evaluate the service quality provided by these systems is an important factor in evaluating the performance of these systems. An important element in the transmission of information to travelers, as part of an ATIS, is the variable message sign (VMS).

In evaluating the service quality by VMS, there are two methods that have been generally used. One is to evaluate the service quality indirectly through the investigation of traffic operational effects. For example, how much does the installation of ATIS along the road increase average vehicle speed or reduce average delay? Investigating these effects is relatively easy, but it is difficult to truly evaluate how drivers perceive the service quality of these devices or how satisfied drivers are with the service they are receiving using these measures of effectiveness (MOEs).

Another way to investigate driver satisfaction of service quality would be to use a survey. For instance, motorists could be asked about their satisfaction with the contents and accuracy of information provided by a VMS. By employing a survey, the service quality and reliability that drivers perceive can be evaluated; however, only basic results, such as a simple percentage or degree of satisfaction relative to each criterion could be provided. These types of results are limited and not really sufficient to represent drivers’ perception of service quality. They cannot represent appropriately the variability and complexity of human perception. Another problem with using a survey method is the
difficulty of describing the survey results quantitatively and objectively because surveys primarily use linguistic terms, not exact quantitative scales, to evaluate a subject’s response and those linguistic terms are determined by subjective human decision making processes. Thusly, there is a need to interpret quantitatively and objectively drivers’ perceptions as indicated in the results of the survey, to aggregate the drivers’ responses to various questions related to VMS service, and to evaluate the overall driver perception of the system.

In the ITS Evaluation Resource Guide, user satisfaction is regarded as one of the measures of effectiveness of mobility. It is also indicated that user satisfaction measures characterize the difference between users’ expectations and experience in relation to a service or product. Relative to this guideline, several evaluations have been performed. Studies of ATIS in Arizona and Missouri (Orban et al. 2000) were conducted in which an analysis of user satisfaction was included. In these studies, simple percentages corresponding to each evaluation criterion were presented as the final results. However, this type of approach does not provide sufficient or meaningful detail relative to making design decisions when contrary findings are indicated. This was similar to the methodology and analysis of ATIS in Pennsylvania (Patten et al. 2003). The major drawback to all of these studies is that they were unable to investigate the individual differences in the participants’ subjective assessment of service quality.

In this study, a method of evaluating VMS service quality based on fuzzy set theory is introduced. Fuzzy sets, where a more flexible sense of membership is possible, are classes with “un-sharp” and vague boundaries. Fuzzy sets theory is a branch of set theory that is useful for the representation of imprecise knowledge of the type that is prevalent in human concept formation and reasoning. Its usefulness lays in the concept that fuzzy theory can represent a type of uncertainty due to vagueness or fuzziness (Yen and Langari 1998). Since L. A. Zadeh developed the concept of fuzzy sets in 1965 (Zadeh 1965), it has been applied in various areas other than transportation engineering to assess user perception. For instance, evaluation of service quality (Ras et al. 1998), studies of operator safety in industrial engineering settings (McCauley and Badiru 1996), or applications for multiple attribute decision making processes (Ribeiro 1996, Juang et
al. 1992) are areas that have been studied using fuzzy approaches. The membership function is the most important element of the fuzzy approach as it makes it possible for fuzzy set theory to be used to evaluate uncertain and ambiguous matters. One of the most important and difficult tasks for applying fuzzy technique is to correctly measure the membership function. In this research, the role of the membership function is to represent an individual and subjective human perception as a member of a fuzzy set. This membership function can represent the degree of the subjective notions of a vague class with an infinite set of values between 0 and 1. In the procedure describe herein, two membership functions for five linguistic scales and an evaluation of the relative importance of six service-related criteria were formulated using results from a survey conducted for this study. The second fuzzy membership function was determined applying Saaty’s eigenvector method (Saaty 1977) which is commonly used in multiple decision making analysis. Individual perceptions of the service were evaluated using results from a previously conducted survey subjected to two fuzzy membership functions.

5.2 Methodology

An evaluation of the ATIS used by the Pennsylvania Turnpike was conducted recently by researchers at the Pennsylvania Transportation Institute (Patten et al. 2003). They conducted both a traffic operational effects study and a driver satisfaction study. For the driver satisfaction study, they employed a mail back survey that was returned by a total of 2,417 respondents (1,528 motorists and 889 truckers). In that part of their study, they investigated how drivers’ perceive the service quality of the ATIS, focusing on three traveler information system elements: VMS, highway advisory radio (HAR) and telephone service. To evaluate those service qualities, each question in the survey consisted of five scales of perception: strongly disagree, disagree, neither agree nor disagree, agree, and strongly agree. As seen in Figure 5-1, they may have been asked what their level of agreement was with a statement such as, “Variable message signs were clearly visible.”
Using those five scales of perception, they were able to investigate how drivers perceive the service quality relative to different attributes of each service type. For example, for VMS, criteria such as visibility (for detection) or legibility (for reading) were used. They computed the percentage of each scale of perception as the final result and concluded as follows:

In general, the motorists felt that the VMS displays were clearly visible and easy to read and understand, and that the information provided was of good quality.

In reaching those conclusions, they simply aggregated the percentage of the “agree” and “strongly agree” responses for each criterion. In this way, the difference in perception between the response of “agree” and “strongly agree” cannot be fully explained. Also, the simple aggregation of the drivers’ response to various questions might ignore the
difference in importance of each criterion as perceived by drivers and lose the unique personal characteristics and preferences for evaluating the drivers’ qualitative perception of the system. Another limitation of this study is that the overall service quality as perceived by all drivers, considering the relative importance of the different criteria and the preferences of the drivers, could not be measured.

To solve those problems, the existing survey results of VMS service quality were re-analyzed using fuzzy sets. For the re-analysis, five steps of fuzzy application were conducted. The first step entailed conducting additional surveys that would yield data for determining the membership functions. The second step involved the construction of the membership functions. The third step evaluated individual perception of VMS service quality using two fuzzy membership functions and the existing survey results. The fourth step necessitated the aggregation of the individual perceptions for analyzing the overall service quality perceived by all drivers. The final step required the defuzzification of the fuzzy set to define a crisp value of service quality. Figure 5-2 shows the whole procedure for evaluating service quality of VMS.
5.2.1 Survey

Having drivers who had responded the original survey take part in the additional survey work was impossible; therefore, it was assumed that the information acquired from the additional survey with new subjects would generally parallel the responses of the original survey. There are six experimental methods commonly used to create a membership
function (Dubois and Prade 2000). These include: polling, direct rating, reverse rating, interval estimation, membership function exemplification, and absolute or pair-wise comparison. Interval estimation was used to construct membership functions of five scales of linguistic statements. Interval estimation is known as the method that is able to yield more appropriate results for continuous measurements. It is also a relatively simple way for determining fuzzy membership function, and membership functions developed using this method are more clear and precise as compared to those developed using the direct rating or polling methods. Saaty’s pair-wise comparison was used to determine the fuzzy weights of the different criteria. Generally, the pair-wise comparison method is known to produce significantly more precise results. However, the pair-wise comparison method can require the use of a survey instrument that is time consuming, which can lead to subject fatigue when they are asked to make comparisons of all criteria, if there are many criteria. To solve this problem, the number of criteria was reduced, and questions using pair-wise comparisons were designed to be simpler and easier to respond to. The six VMS evaluation criteria used in the study are: visibility, legibility to read, comprehension of message displayed, accuracy of information, usefulness of information, and correspondence between information displayed and expected by driver. The survey was conducted with 42 subjects who are licensed drivers with some highway driving experience.

5.2.2 Construction of Fuzzy Membership Functions

As mentioned above, two membership functions were constructed including five scales of linguistic statement and the importance of the weight of six criteria. The type of membership function, such as a triangular, trapezoidal, or $\pi$-curve function, was determined after an initial review of the data. The first membership function representing five scales of linguistic statements was created by the ranges with crisp values from the result of the interval estimation. The second set of membership functions, the fuzzy weights of the six criteria, was constructed using the eigenvector method developed by Saaty, which was explained in greater detail in the section 4.3.
The weights of the criteria, which are determined by the eigenvector method, are crisp numbers, and they are estimated using the one response. However, \( n \) sets of the weights estimated using all survey responses can create the fuzzy numbers and the membership function representing the fuzzy weight of the criteria.

### 5.2.3 Evaluation of Individual Perception of VMS Service Quality

The individual perception of VMS service was computed by applying the concept of fuzzy weight average with combinatorial interval analysis as following equation (Eq. 5.1):

\[
Perception_{VMS_j} = \frac{\sum_{k=1}^{6} (w_k \otimes A_{jk})}{\sum_{k=1}^{6} w_k}
\]

where

- \( Perception_{VMS_j} \) = the perception of VMS service perceived by a participant \( j \),
- \( k \) = the criterion of VMS including visibility, legibility, comprehension, accuracy, usefulness and correspondence,
- \( w_k \) = the normalized fuzzy weight of criteria (\( \sum w_k = 1 \)),
- \( A_{jk} \) = the fuzzy number representing the individual opinion of VMS regarding criteria
- \( k \), and \( \sum_{k=1}^{6} \) and \( \otimes \) = fuzzy operations using \( \alpha \) – cut interval analysis.

This concept, the fuzzy weighted average method, was explained in greater detail in the section 4.2. For the study at hand, three \( \alpha \)- values were selected, including 0, 0.5 and 1, to find the intervals. Individual fuzzy numbers (322 in all), which represent individual perceptions of 322 drivers, was calculated using a combinatorial interval analysis in Matlab. The Matlab program is included in Appendix B.
5.2.4 Aggregation of the Individual Perceptions

The 322 individual perceptions of VMS service evaluated above should be aggregated to represent the group’s overall opinion. For aggregating the fuzzy number of the perceptions, a “arithmetic mean” of the fuzzy numbers, which represent all individual perceptions, were calculated using a fuzzy average operation based on the “α-cut” concept of fuzzy sets and an interval analysis. The outputs from this step are still fuzzy numbers, and they should be transformed into crisp numbers to be more easily understood.

5.2.5 Defuzzification

To transform the final fuzzy set that represents the group’s overall opinion into crisp numbers, a defuzzification procedure was conducted. Out of several defuzzification methods, the defuzzified method developed by Juang, et al. (Juang et al. 1992) was used due to its simplicity and ease of computation. It is a mapping model for measuring fuzzy numbers using estimated utility as following equation (Eq. 5.2):

\[ u = \frac{(A_L - A_R + 1)}{2} \]  

Eq. 5.2

where

\( u \) = the utility to measure or rank a fuzzy number,
\( A_L \) = the area enclosed to the left of the characteristic function that characterizes the fuzzy number,
\( A_R \) = the area enclosed to the right of the characteristic function that characterizes the fuzzy number,

The utility yields a value between 0 and 1, and the higher utility value indicates the higher service quality of VMS.
Through these procedures, the survey results from the prior study, which consisted of simple percentages, were converted to an overall measure of service quality that takes into consideration the variance of human perception and the degree of importance of the six criteria. The final number represents the overall service quality perceived by all drivers.

5.3 Application of Methodology

5.3.1 Construction of Membership Functions

As mentioned previously, the types of fuzzy membership function were determined after a review of the data. To find the first membership functions for five scales of linguistic statements, the universe interval, from 0 to 1.0, was partitioned with unit length (0.05) intervals. Then normalized frequencies of each unit interval were calculated. The shapes of the histograms derived from these normalized frequencies indicated that a trapezoid membership function was the most appropriate type of membership function for representing five scales of linguistic statements. Juang et al. (1993) indicated that a trapezoidal membership function is commonly used to represent a fuzzy interval estimate. The trapezoidal membership function is specified by four parameters \( \{a, b, c, d\} \) as following mentioned in Table 2-2. Finally, to determine the membership function, three rules for designing the membership function (Yen and Langari 1998) were considered:

Rule 1: Each membership function overlaps only with the closest neighboring membership functions

Rule 2: For any possible input data \((x)\), its membership values in all relevant fuzzy sets should sum to one or nearly so.

Rule 3: The range of top of trapezoid should be approximately matched with the standard deviation of the input value, \(x\).
Figure 5-3 shows the fuzzy membership functions constructed through the procedures described above and their parameter values. The second set of membership functions, which represent the fuzzy weight of six criteria, was created by the 23 sets of weights evaluated by Saaty’s eigenvector method as mentioned above. Table 5-1 shows the PCM and weights judged by an individual response as an example. This procedure was repeated with all of the survey results, which created 23 PCMs and sets of weights. Review of the data indicated that triangular fuzzy membership functions were the most suitable type of membership function for representing the weights of the six criteria. A triangular membership function is specified by three parameters \( \{a, b, c\} \), and the precise appearance of the function is determined by the choice of parameters as mentioned in Table 2-2.

![Figure 5-3: Fuzzy Membership Function of Five Scales Linguistic Statement.](image)
These three parameters were finally determined using the min, modal, and max values. Figure 5-4 shows the second set of fuzzy membership functions. As can be seen in the figure, drivers regard comprehension, accuracy, and usefulness of VMS as being more important than visibility, legibility to read, and correspondence to their expectance. This result is similar to an earlier study of criteria for traffic sign design and evaluation (Dewar 1988). In this study, Dewar conducted a survey that examined the relative importance of criteria used for traffic sign design and evaluation and indicated that the criteria related to the content of a traffic sign (e.g. understandability) were more important than the criteria related to visibility and identification (e.g. legibility or reaction time).

<table>
<thead>
<tr>
<th></th>
<th>Visibility</th>
<th>Legibility</th>
<th>Comprehension</th>
<th>Accuracy</th>
<th>Usefulness</th>
<th>Correspondence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Visibility</td>
<td>1</td>
<td>5</td>
<td>1</td>
<td>1/5</td>
<td>1/5</td>
<td>1/3</td>
</tr>
<tr>
<td>Legibility</td>
<td>1/5</td>
<td>1</td>
<td>¼</td>
<td>1/5</td>
<td>1/4</td>
<td>1</td>
</tr>
<tr>
<td>Comprehension</td>
<td>1</td>
<td>4</td>
<td>1</td>
<td>1/4</td>
<td>1/5</td>
<td>5</td>
</tr>
<tr>
<td>Accuracy</td>
<td>5</td>
<td>5</td>
<td>4</td>
<td>1</td>
<td>1</td>
<td>7</td>
</tr>
<tr>
<td>Usefulness</td>
<td>5</td>
<td>4</td>
<td>5</td>
<td>1</td>
<td>1</td>
<td>7</td>
</tr>
<tr>
<td>Correspondence</td>
<td>3</td>
<td>1</td>
<td>1/5</td>
<td>1/7</td>
<td>1/7</td>
<td>1</td>
</tr>
</tbody>
</table>

\[ \lambda_{\text{max}} = 7.011 \]

\[ (A - \lambda_{\text{max}} \cdot I) \cdot W = 0 \]

\[ W_i = \{w_{i1}, w_{i2}, w_{i3}, w_{i4}, w_{i5}, w_{i6}\} = \{0.085, 0.045, 0.127, 0.331, 0.343, 0.070\} \]
5.3.2 Individual Perception of the VMS Service Quality

The results of the original survey, which consisted of a five point scale, can be seen Table 5-2 Out of 1,528 motorist data sets, 322 data sets were selected for use after removing those that contained uncompleted responses. This scale, which represents each level of “agreement” with an integer, was transformed into a fuzzy number using the first fuzzy membership function. The individual perceptions transformed as fuzzy sets were aggregated by the fuzzy weighted average based on extended algebraic operations and $\alpha$-
cuts representation. To illustrate the process of evaluating the individual perception of VMS service, a response of the first participant in Table 5-2 is used. The response can be represented by fuzzy sets as follows:

Perception regarding visibility (5) = \{0.0/0.75, 0.5/0.85, 1.0/0.95, 1.0/0.95\}
Perception regarding legibility (1) = \{1.0/0, 1.0/0.1, 0.5/0.15, 0.0/0.2\}
Perception regarding comprehension (1) = \{1.0/0, 1.0/0.1, 0.5/0.15, 0.0/0.2\}
Perception regarding accuracy (1) = \{1.0/0, 1.0/0.1, 0.5/0.15, 0.0/0.2\}
Perception regarding usefulness (1) = \{1.0/0, 1.0/0.1, 0.5/0.15, 0.0/0.2\}
Perception regarding correspondence (1) = \{1.0/0, 1.0/0.1, 0.5/0.15, 0.0/0.2\}

\[
\text{Perception of } \text{VMS}_i = \frac{\sum_{k=1}^{6} (w_k \otimes A_{ik})}{\sum_{k=1}^{6} w_k}
\]

### Table 5-2: Results of the Original Survey Representing the Satisfaction of VMS in PA Turnpike

<table>
<thead>
<tr>
<th>#</th>
<th>Visibility</th>
<th>Legibility</th>
<th>Comprehension</th>
<th>Accuracy</th>
<th>Usefulness</th>
<th>Correspondence</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>5</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>5</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>1</td>
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<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>J</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>...</td>
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<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>322</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>

* 1: Strongly Disagree, 2: Disagree, 3: Neither agree nor disagree, 4: Agree, and 5: Strongly Agree
Repeating this procedure created 322 fuzzy numbers representing the 322 individual perceptions of VMS. Those 322 fuzzy numbers were aggregated to represent the group’s overall opinion using the concept of the arithmetic mean as mentioned previously. Table 5-3 shows some of the individual perceptions and the corresponding arithmetic mean values, and Figure 5-5 shows the final fuzzy set representing the group’s overall opinion. This final fuzzy set, \( \{0.0/0.12, 0.5/0.30, 1.0/0.52, 1.0/0.58, 0.5/0.959, 0.0/0.992\} \), is transformed to crisp number that can be more easily understood using the defuzzified method as follows:

\[
\begin{align*}
  u = 100 \cdot \frac{A_L - A_R + 1}{2} = 100 \cdot \frac{0.322 - 0.214 + 1}{2} = 55.4
\end{align*}
\]

This final number, 55.4, indicates the degree of satisfaction with VMS service as perceived by a group of participating drivers taking into consideration the variance of human perception and the degree of importance of the six criteria. While not a typical validation, the results of the original study and results using a classical weighted average were examined and compared with the result of the proposed method.
The original study provided the percentages of several criteria giving a rating of either “agree” or “strongly agree”. If those percentages are aggregated to represent
overall satisfaction of VMS perceived by most of drivers, the mean of the percentages is 68.7. If the importance of each criterion is considered, then the classical weighted average method, which is commonly used in multiple decisions making processes, can be applied. The weight values were determined by finding sets of normalized eigenvectors corresponding to the largest eigenvalue in the PCMs from survey results. These sets of weights were used to determine fuzzy weight values described previously. To calculate the conventional weighted average, the mean of the weights representing the importance of each criterion was used. The weighted average using this procedure is 68.8.

These values are different from the result coming from the proposed method. The reasons for this difference may be because the original study did not consider following elements:

- the difference in perception between the response of “agree” and “strongly agree,”
- the difference in importance of each criterion as perceived by drivers, and
- the unique personal characteristics and preferences for evaluating the drivers’ qualitative perception of the system.

5.4 Conclusion

In this paper, quality of VMS service was evaluated using the fuzzy approach. Generally, quality of service is a significant indicator in evaluating the performance of transportation facilities. However, it is difficult to be measure because the quality of service that a human perceives is affected by various factors, and it is represented well in qualitative linguistic terms, but not quantitatively. Current approaches for evaluating the service quality of transportation facilities are limited because human thinking is subjective and complicated, and human perception cannot be represented by binary or numerical information. The proposed method makes numerical evaluation of service quality feasible.

To apply this method, two fuzzy membership functions were determined through a survey. Many previous studies did not concentrate on the construction of the fuzzy
membership function, even though this is the most significant step for fuzzy applications. In this paper, the first membership function, which represents five scales of linguistic statements, was constructed using the interval estimation method. The second set of fuzzy membership functions, which represent the importance of the weight of six criteria for evaluating VMS service quality, were determined using Saaty’s eigenvector method. Quality of VMS service perceived by an individual driver was evaluated using the fuzzy weight average. A set of 322 quality measures were computed, and they were aggregated and transformed to one number using the arithmetic fuzzy mean. The defuzzified final value indicates the degree of satisfaction with VMS service that was perceived by the participating drivers. This value takes into consideration the variance of human perception and the degree of importance of the six criteria.

This study was envisioned as a “frontier” or “proof of concept” study - the application of fuzzy sets to evaluate user perception of service quality of VMS. This paper demonstrates the possibility and advantages of applying fuzzy sets to evaluate user perception of transportation service quality. However, the method as presented herein needs to be developed further. As the original survey was conducted without using fuzzy concepts and having drivers who had responded the original survey take part in the additional survey work was impossible, an assumption that the information acquired from the additional survey with new subjects would generally parallel the responses of the original survey was used. Therefore further research is needed to design and conduct surveys for evaluating quality of service using the concept of fuzzy set theory. In this paper, the fuzzy membership functions determined are special functions that can only be used for evaluating this specific VMS service. However, to generalize this method, a universal membership function that can be used in other problems should be determined. Also, the effect of different questions or scales should be considered. It may be possible to develop this universal membership function for the fuzzy weight of the evaluation criteria using approaches such as Neural-fuzzy logic modeling. Furthermore, through extensions, the quality of service of other transportation facilities could also be evaluated using a method similar to the one described herein. Also a standard validation procedure should be conducted in the future to prove that the proposed method can produce more
accurate results. Other modifications will allow the method to be used more easily in practice.
CHAPTER 6

INCORPORATION OF TRANSPORTATION EXPERTS’ OPINIONS OF MEDIAN SAFETY USING A HIERARCHICAL FUZZY INFERENCE SYSTEM

6.1 Introduction

A transportation expert may be asked to support a decision, determine a preference, rank influencing factors, or assess alternatives through various methods including surveys, interviews, panel meetings, and expert analyses. In many of these cases, before the experts render their opinion they formulate it through the use of linguistic information and their own subjective decision criteria. An efficient method to analyze subjective and linguistic information employed by people, whether expert or layman, is to apply a fuzzy set concept. The primary strength of a fuzzy approach is that it is applicable for the analysis of human knowledge and subjective human perception, which are represented by linguistic terms rather than numerical terms, and the deductive process. Various applications of fuzzy sets have been applied to analyze many types of information, such as fuzzy decision making analyses, fuzzy aggregation methods, and fuzzy inference systems. The fuzzy inference system, which mimics the human perception and decision making processes, is a deductive process of mapping given inputs to certain outputs based on fuzzy membership functions and fuzzy rules. It has been widely applied in various analyses of subjective and ambiguous information.

In this study, a new approach to incorporate transportation experts’ opinions using the hierarchical fuzzy inference system (HFIS) is proposed. The proposed fuzzy approach is applied to incorporate transportation expert opinions regarding median safety gathered as part of a previous study. This earlier median safety study used a Delphi survey technique to gather expert opinions on various factors and median scenarios that may influence cross median collision (CMC) crash likelihood. Through the incorporation of the experts’ opinion using HFIS, a median safety index was produced, and it was
compared with observed median crash data to validate the results from the proposed HFIS.

6.2 A Hierarchical Fuzzy Inference System

Fuzzy inference systems have been applied in various areas. However, many studies reported limitations of the conventional fuzzy inference system when dealing with multiple variables (Raju et al. 1991, Lee et al. 1995, Chen and Parng 1996, and Wang 1999). The number of rules in a conventional fuzzy system increases exponentially with the number of variables involved. Normally, three or four variables are the maximum number that can be considered as part of a conventional fuzzy inference system. One of the ways to solve this “rule-explosion problem” is to use a fuzzy inference system with a hierarchical structure called a hierarchical fuzzy system. The hierarchical fuzzy system, proposed by Roju et al. (1991), can reduce the computational complexity of a multivariable fuzzy system and the number of rules.

This rule explosion problem is more complex when fuzzy logic is applied to study transportation user perception. This is because transportation user perception regarding transportation service or safety is usually affected by many factors, such as roadway geometry, traffic flows, driver characteristics, and other driving conditions. It may not be able to be determined by only a few factors. Also, each driving condition has many sub-elements. For example, geometric conditions consist of many measures of cross-section elements, horizontal and vertical alignment, and roadside environments.

6.3 Measure of Median Safety Based on a Hierarchical Fuzzy Inference System

6.3.1 Selection of Variables

In a 2001 study of median safety, Donnell, et al. investigated median safety on Interstates and expressways (Donnell et al. 2002, and PTI and MRI 2000). They conducted surveys
with 23 transportation experts to collect their opinions regarding which factors have the greatest influence on CMC. They found that median width, operating speed, horizontal curvature, median cross-slope, and shoulder width were the five highest ranked factors out of 10 geometric factors influencing CMCs as shown in Table 6-1. Ranking 1 indicated the factor with the greatest influence, and ranking 10 indicated the factor with the lowest influence. In their study, crash data and roadway inventory data for five years (1994 to 1998) were also collected from two Pennsylvania Department of Transportation (PennDOT) databases: the Roadway Management System (RMS) and Crash Reporting System (CRS). These databases were merged to create a “median safety” database.

Table 6-1: Mean and Standard Deviation of Geometric Factors Influencing Median Crossover Crashes.

<table>
<thead>
<tr>
<th>Factor</th>
<th>Mean of rankings*</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Median Width</td>
<td>2.20</td>
<td>1.94</td>
</tr>
<tr>
<td>Operating Speed</td>
<td>2.60</td>
<td>1.31</td>
</tr>
<tr>
<td>Horizontal Curvature</td>
<td>3.80</td>
<td>2.26</td>
</tr>
<tr>
<td>Median Cross-Slopes</td>
<td>4.00</td>
<td>1.89</td>
</tr>
<tr>
<td>Shoulder Design</td>
<td>5.90</td>
<td>2.27</td>
</tr>
<tr>
<td>Superelevation Rate</td>
<td>6.85</td>
<td>1.90</td>
</tr>
<tr>
<td>Shoulder Slope</td>
<td>7.05</td>
<td>2.33</td>
</tr>
<tr>
<td>Pavement Friction</td>
<td>7.10</td>
<td>2.05</td>
</tr>
<tr>
<td>Median Surface</td>
<td>7.15</td>
<td>2.30</td>
</tr>
<tr>
<td>Vertical Curvature</td>
<td>8.35</td>
<td>2.13</td>
</tr>
</tbody>
</table>

*: It is the mean of rankings that 23 experts ranked out of 10 geometric factors.

To select variables to be used for the fuzzy inference system, the five highest ranked variables and the variables for which data were available in the median safety database were considered. Since the crash data were used for corroborating the results of the proposed fuzzy inference system, the availability of each variable in the database was
also a critical issue in this variable selection procedure. Additionally, current design manuals were reviewed to select relevant variables for the fuzzy inference system. For the current median barrier warrant in the AASHTO Roadside Design Guide (AASHTO 1996), ADT and median width are employed. These two variables have been known as the most critical factors in assessing median safety. From these reviews, five variables to evaluate geometric conditions and one variable to evaluate traffic flow conditions were selected. The five geometric variables were median width, horizontal curvature, operating speed, median cross-slope, and shoulder width. ADT was used to describe the traffic flow condition.

6.3.2 Construction of Fuzzy Membership Functions

There are various ways to determine fuzzy membership functions. Generally, the methods of formulating fuzzy membership functions can be classified into three approaches: constructing the membership functions through the analyst’s judgment, constructing the membership functions through experiments, or constructing the membership functions from a given numerical data set. Selecting a method to determine the membership functions depends on many conditions including the characteristics of the study and the available data set associated with the study.

In this study, the method based on analyst’s judgment was used to determine the fuzzy membership functions. It is the most common means used to construct fuzzy membership functions because of its simplicity and wide applicability. In this method, an analyst employs their own knowledge and information gleaned from relevant literature to compose the membership functions. In the proposed study, fuzzy membership functions for the selected variables were constructed through four resources: the authors’ own knowledge; a review of the experts’ opinion; a review of the literature and the state-of-the-practice related to transportation safety, typically median safety; and a basic review of the roadways for which crash data were collected. A review of relevant literature and associated practice is usually the most significant resource for determining reasonable and appropriate fuzzy membership functions in the analyst intuition method. Since there
are few studies that have investigated the relationship between controlling factors and CMC, the general safety effects of the selected variables were also reviewed. Through a review of the experts’ opinion regarding the influence of the various factors on median safety, the relative importance of each factor was investigated. This relative importance was used to determine the weight of each variable. A basic review of the roadways within the crash database was conducted without any statistical analysis. The variable type (e.g., binary, continuous), the number of classes for each variable, and the range of values were mainly considered in this review.

Using these resources, two types of fuzzy membership functions were determined. The first fuzzy membership functions represented how significantly each factor influences median safety. The second fuzzy membership functions represented the relative importance of each geometric factor.

**6.3.2.1 Fuzzy Weight of Five Geometric Factors**

The fuzzy membership functions for the weights of five geometric variables were determined using the ranking of geometric elements influencing median safety as evaluated by 23 transportation experts in the previous study. Each ranking was aggregated and converted to a normalized value ranging from 0 to 1.0. A review of the literature and the converted ranking data indicated that triangular fuzzy membership functions were the most suitable type of membership function for the weights of the five geometric variables (Lee et al. 2005). A triangular membership function is specified by three parameters \(a, b, c\). These three parameters were determined based on the minimum, modal, and maximum values. Figure 6-1 shows the set of fuzzy weights of the five geometric variables.
Figure 6-1: Fuzzy Weights for Five Geometric Factors.
6.3.2.2 Fuzzy Membership Function for the Factors Controlling Median Safety

The initial construction of the fuzzy membership function for the six factors influencing median safety was accomplished through the review of references and common engineering judgment. They were then slightly modified to reflect Pennsylvania Interstate highways or expressways because the review results represented general or universal information regarding driving environments and not specifically the driving environments of Pennsylvania. The review results, which allowed for the construction of the preliminary fuzzy membership function, are explained in the paragraphs below.

The first variable, average daily traffic (ADT), represents the traffic condition. ADT is known as a significant factor influencing median safety, and it is used as one of two criteria of the median barrier warrant. The median barrier warrant in the AASHTO Roadside Design Guide uses two categories to determine the barrier installation guideline. For ADTs less than 20,000, barrier is optional, but for ADTs greater than 20,000, barrier is warranted, depending on the median width. This category is also applied in the PennDOT design manual (PennDOT 1998). In the expert survey, four categories: 15,000 to 30,000, 30,000 to 50,000, 50,000 to 75,000, and greater than 75,000, were considered to investigate the safety effects of the traffic flow condition.

The second variable is median width which represents a geometric condition. Median width is one of the most significant factors used to evaluate median safety in conjunction with ADT. To determine the fuzzy membership function for median width, AASHTO’s A Policy on Geometric Design of Highways and Streets (the Green Book), AASHTO’s Roadside Design Guide, and other references were reviewed. The 2001 Green Book indicates that median widths of 50 to 100ft are common on rural freeways (AASHTO 2001). In AASHTO’s Roadside Design Guide, median barrier warrant is based on three categories of median width. Barrier is warranted for medians less than 30ft, and barrier is not considered for medians greater than 50ft. Barrier is optional for medians between 30 and 50ft.

Garner and Deen investigated the relationship between elements of median design and accident occurrence (Garner and Deen 1973). In their study, they indicated that
accident rate decreased with an increase in the median width up to 30 to 40 feet, at which point the accident rate started to level off. The results of their study indicated that median widths should be at least 40 feet to improve median safety significantly.

Kniuman et al. also investigated the association of median width and highway accident rates (Knuiman et al. 1993). In their study, a relationship between median width and accident rate was found in Utah and Illinois. The general results of this study indicated that accident rates decreased as the median width was increased. Their results showed that large numbers of accidents were recorded for medians with widths less than 30 ft and a low number of accidents at medians with width greater than 50 ft.

There are two studies that developed statistical prediction models for CMCs. Donnell and his colleagues investigated the association between CMCs and roadway environments and developed a statistical crossover crash prediction model (Donnell et al. 2002). Donnell also proposed a new barrier warrant in his doctoral dissertation, which paralleled the other research, based on his analysis results (Donnell 2003). His proposed barrier warrant also has three categories of median width (less than 30 ft, between 30 and 70 ft, and greater than 70 ft). These three categories are different from that of AASHTO’s Roadside Design Guide. Another study based on statistical modeling for CMC was the Washington State study. Songrit at al. developed another statistical prediction model and investigated the effectiveness of median barriers (Songrit 2004). Their results indicated that the variable of median width has a significant impact on CMC frequency. Sections with a median width of less than 60 ft were expected to experience twice the frequency of CMCs, controlling for other factors, than those with median widths in excess of 60 ft. They also recommended considering medians with widths narrower than 50 ft for mandatory barrier installation and not installing barriers for medians that are wider than 60 ft. In the 50 to 60 ft range, it is recommended that sections be evaluated on a case by case basis. As a result of the literature reviews, it appears that 30 ft, 50 ft or 60 ft, and 70 ft of median width are the critical median widths. These critical median widths were applied in the determination of the fuzzy membership functions.

The third variable, horizontal curvature, represents a geometric condition. The safety effect of horizontal curvature has been investigated in many studies. Statistical
analysis by Zegeer et al. found significantly higher curve accidents for: sharper curves, narrower lane widths on the inside of a curve, lack of spiral transitions, and increased superelevation deficiency (Zegeer 1992). Hauer investigated the safety consequences of selecting the degree of horizontal curvature. He indicated that increasing the degree of curve always increases the expected accident frequency (Haur 1999). Its effect is aggravated by large deflection angles. Though these studies investigated the safety of rural highways, not expressways, and the safety effect on all types of curve crashes not just cross median crashes, the results of the studies emphasize that various features of horizontal curvature can affect roadway safety. Under these circumstances, the fuzzy membership functions representing the effect of horizontal curvature on median safety should be determined by taking into consideration various features of a horizontal curve. Three condition levels have commonly been used for evaluating the effect of horizontal curves on safety, such as poor, fair, and good, in previous studies (Zegeer et al. 1981, Zegeer et al. 1988, and Zegeer et al. 1994). However, the median crash data used for comparison with the safety index evaluated by the proposed fuzzy logics included only the presence of horizontal curvature as binary information, such as 0 for no curve and 1 for a curved alignment. Due to this limitation of the database, the fuzzy membership functions representing the effect of horizontal curve on median safety were determined with just two levels in this study such as without curve effect and with curve effect even though it is not as desirable as the multi-condition level described above.

The fourth variable is operating speed representing a geometric condition. Operating speed is another critical factor influencing median safety. The 2001 Green Book indicates that the design speed should not be less than 50mph for an urban freeway or 70mph for a rural freeway. It also recommends that a design speed of 70mph is desirable because higher design speeds are closely related to the overall quality and safety of a facility. The design speed is not always the same as the operating speed, but these two speeds are relatively similar and have a significant association.

The fifth variable is median cross slope. The transportation experts indicated that the effect of median cross slope on median safety was relatively significant out of 10 selected geometric factors influencing CMC. The 2001 Green Book states that median
cross slopes should be preferably 6:1, but slopes of 4:1 may be adequate. Zegeer et al. investigated the accident effects of side slope and other cross-sectional elements (Zegeer et al. 1994). They indicated that flatter side slopes of 3:1 to 7:1 were found to be related to lower rates of single vehicle accidents. However, the median cross slope data in the crash database was also binary data with 0 indicating flatter than 6:1 and 1 indicating steeper than 6:1. This limitation of the median crash database necessitated the creation of two levels of fuzzy membership functions, such as poor and acceptable or steeper and flatter for median cross slopes steeper than 6:1 or flatter than 6:1, respectively.

The last variable is shoulder width. It is the geometric factor with the lowest ranking of the five highest ranked factors (see Table 1). An earlier study by Zegeer et al. investigated the effects of lane and shoulder width on accident reduction (Zegeer et al. 1981). They found that road segments with shoulders wider than two meters had relatively few crashes compared to narrower shoulders. Zegeer used three and two categories of shoulder width, respectively, to investigate the safety effect of shoulder width in a 1988 and a 1994 study (Zegeer et al. 1988 and Zegeer et al. 1994). The three categories of shoulder width were 0 to 3 ft, 4 to 5 ft, and 6 to 13 ft, and the two categories of width were 0 to 4 ft and larger than 5 ft. Figure 4 shows the final fuzzy membership functions of the six controlling median safety factors based on the review results with slight modification to reflect better Pennsylvania Interstate highways or expressways. Table 6-2 shows the summary of the review results.
Table 6-2: The Review Results of References related to Safety Effect of Selected Six Variables.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Study</th>
<th>Review Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADT</td>
<td>Roadside Design Guide</td>
<td>Two categories are used to determine the barrier installation guideline.</td>
</tr>
<tr>
<td></td>
<td>PennDOT Design Manual</td>
<td>- ADT $\leq 20,000$: barrier is optional</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- ADT $&gt; 20,000$: barrier is warranted, depending on the median width</td>
</tr>
<tr>
<td></td>
<td>PTI and MRI(2000)</td>
<td>Four categories: 15,000 to 30,000, 30,000 to 50,000, 50,000 to 75,000, and greater than 75,000, were considered to investigate the safety effects.</td>
</tr>
<tr>
<td>Median Width</td>
<td>2001 Green Book</td>
<td>Median widths of 50 to 100ft are common on rural freeways</td>
</tr>
<tr>
<td></td>
<td>Roadside Design Guide</td>
<td>Three categories are used to determine the barrier installation guideline.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Median width $\leq 30ft$: barrier is warranted</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- 30ft $&lt;\text{Median width} \leq 50ft$: barrier is optional</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Median width $&gt; 50ft$: barrier is not considered</td>
</tr>
<tr>
<td></td>
<td>Garner and Deen (1973)</td>
<td>Accident rate decreased with an increase in the median width up to 30 to 40 feet, at which point the accident rate started to level off.</td>
</tr>
<tr>
<td></td>
<td>Kniuman et al. (1993)</td>
<td>Large numbers of accidents at medians with widths less than 30 ft and a low number of accidents at medians with width greater than 50ft.</td>
</tr>
<tr>
<td></td>
<td>Donnell (2003)</td>
<td>Three categories proposed for barrier warrant (less than 30ft, between 30ft and 70ft, greater than 70ft).</td>
</tr>
<tr>
<td></td>
<td>Songrit et al. (2004)</td>
<td>Sections with a median width of less than 60ft were expected to experience twice the frequency of CMCs, controlling for other factors, than those with median widths in excess of 60ft (less than 50ft, between 50ft and 60ft, greater than 60ft).</td>
</tr>
<tr>
<td>Horizontal Curvature</td>
<td>Zegeer et al. (1992)</td>
<td>Significantly higher curve accidents for: sharper curves, narrower lane widths on the inside of a curve, lack of spiral transitions, and increased superelevation deficiency</td>
</tr>
<tr>
<td></td>
<td>Hauer (1999)</td>
<td>The degree of curve always increases the expected accident frequency.</td>
</tr>
<tr>
<td>Operating Speed</td>
<td>2001 Green Book</td>
<td>The design speed should not be less than 50mph for an urban freeway or 70mph for a rural freeway. It also recommends less than 45mph as low speed and greater than 50mph as high speed.</td>
</tr>
<tr>
<td>Median Cross Slope</td>
<td>2001 Green Book</td>
<td>Median cross slopes should be preferably 6:1, but slopes of 4:1 may be adequate</td>
</tr>
<tr>
<td></td>
<td>Zegeer et al. (1988)</td>
<td>Flatter side slopes of 3:1 to 7:1 were found to be related to lower rates of single vehicle accidents.</td>
</tr>
<tr>
<td>Shoulder Width</td>
<td>Zegeer et al. (1981)</td>
<td>Road segments with shoulders wider than two meters had relatively few crashes compared to narrower shoulders.</td>
</tr>
<tr>
<td></td>
<td>Zegeer et al. (1988)</td>
<td>Three categories were used to investigate the safety effect of shoulder width (0 to 3 ft, 4 to 5 ft, and 6 to 13 ft).</td>
</tr>
<tr>
<td></td>
<td>Zegeer et al. (1994)</td>
<td>Two categories were used to investigate the safety effect of shoulder width (0 to 4 and larger than 5ft).</td>
</tr>
</tbody>
</table>
However, the creation of the fuzzy membership function for horizontal curvature and median cross slope was restricted to reflect the review results. The previous studies emphasized that various features of horizontal curvature can affect roadway safety as mentioned above. Given their findings, the fuzzy membership functions representing the effect of horizontal curvature on median safety should be determined by taking into consideration various features of a horizontal curve. Three condition levels, poor, fair, and good, have commonly been used for evaluating the effect of horizontal curves on safety in previous studies (Lamm et al. 1988, Lamm et al. 1994, and Al-Masaeid 1995). However, the median crash data used for comparison with the safety index, which is based on the proposed fuzzy inference system, included only the presence of horizontal curvature as binary information, such as 0 for no curve and 1 for a curved alignment. Due to this limitation of the database, the fuzzy membership functions for horizontal curvature were determined with just two levels in this study even though it is not as desirable as the multi-condition level described above. The median cross slope data in the crash database was also binary data with 0 indicating flatter than 6:1 and 1 indicating steeper than 6:1. This limitation of the median crash database necessitated the creation of two levels of fuzzy membership functions, such as poor and acceptable or steeper and flatter for median cross slopes steeper than 6:1 or flatter than 6:1, respectively. Figure 6-2 shows the final fuzzy membership functions of the six controlling median safety factors based on the review results with slight modification to reflect better Pennsylvania Interstate highways or expressways.
Figure 6-2: The Fuzzy Membership Function of Six Influencing Factor on Median Safety.
6.3.3 Two Levels of Hierarchical Fuzzy Inference System

A fuzzy inference system with many variables is difficult to generate. To reduce the complexity of a multivariable fuzzy system, the proposed fuzzy system with six variables was decomposed into two subsystems: a system representing traffic conditions and a system representing geometric conditions. It was developed as a HFIS with two levels: a lower level fuzzy system and an upper level fuzzy system.

The lower level of the fuzzy inference system was generated to infer and represent overall geometric conditions produced by each geometric factor. The five geometric factors used as input variables were median width, horizontal curvature, operating speed, median cross slope, and shoulder width. The final output of this lower level fuzzy system was called as the Fuzzy Geometric Index (FGI). A high value of FGI means poor driving conditions regarding geometric features and indicates that more median crashes are likely to happen. This output of the lower level fuzzy system was used as one of the input variables for the upper level fuzzy system. Meanwhile, the upper level fuzzy system was generated to infer and represent the overall level of median safety with two input variables: FGI and traffic flow. The final output of the fuzzy inference system represents how safe roadways are with respect to median safety. A higher value indicates a higher likelihood cross median crash. Figure 6-3 shows the structure of the proposed hierarchical fuzzy inference systems for median safety. Figure 6-4 shows the reduction of the number of fuzzy rule generated in the hierarchical fuzzy inference system. This fuzzy inference system was embodied using MATLAB. The MATLAB program is included in Appendix C.
Figure 6-3: Proposed Hierarchical Fuzzy Inference Systems for Median Safety.
Hierarchical Fuzzy Inference System
(if-then rule)

ADT

Traffic Flow Condition
Low Medium High V. High

Median Width
Poor Fair Good

Horizontal Curvature
Without Curve Effect With Curve Effect

Operating Speed
Low Medium High

Median Cross Slope
Acceptable Poor

Shoulder Width
Poor Fair Good

Fuzzy Geometric Index
Good V. Poor

Fuzzy Median Safety Index
Good Fair Poor V. Poor

16 fuzzy rules should be generated (4^2=16).

108 fuzzy rules should be generated
(3 × 2 × 3 × 2 × 3=108).

Lower level fuzzy inference system

Upper level fuzzy inference system

Note: If non hierarchical fuzzy inference system is applied, 432 fuzzy rules should be generated.

Figure 6-4: Reduction of the Number of Fuzzy Rule Generated in the Hierarchical Fuzzy Inference System.
To build fuzzy inference systems for both hierarchical levels, the Mamdani inference system, which is one of the most widely used and uses “max-min inference,” was employed. The Mamdani inference system uses rules whose consequent part is also fuzzy sets (Yen and Langari 1998):

\[
R_i : \text{IF } X_1 \text{ is } A_{i1} \text{ and } X_2 \text{ is } A_{i2} \text{ and } \ldots \text{ and } X_n \text{ is } A_{in} \text{ THEN } Y \text{ is } C_i
\]

\((i = 1, 2, 3, \ldots m)\)

where

- \(m = \) the number of fuzzy rules,
- \(X_j (j = 1, 2, \ldots, n)\) are the input variables,
- \(Y = \) the output variable, and \(A_{ij}\) and \(C_i\) are fuzzy sets for \(X_j\) and \(Y\), respectively.

Output represented by fuzzy sets is computed by the following relational composition (Eq. 6.1):

\[
u_{e_{C_i}}(Y) = \max\{u_{e_{C_i}}(Y), \min[u_{i1}(x_{i1}), u_{i2}(x_{i2}), \ldots, u_{in}(x_{in})]\}\]

\[\text{Eq. 6.1}\]

where

- \(x_{ij} = \) a input value for each variable,
- \(u_{e_{C_i}}(Y) = \) a consequent fuzzy membership function
- \(u_{e_{C_i}}(Y) = \) a implicated fuzzy membership function.

As Hamad and Kikuchi noted, the final value of an engineering application of fuzzy inferences is requested as a single value due to the common characteristic of engineering problems (Hamad and Kikuchi 2002). Therefore, a “defuzzification” procedure is necessary as shown in figure 1. In this study, the “Center-of Area (COA)” method, which is the most popular defuzzification technique and is also referred to as the “Center-of Gravity,” was used as following equation (Eq. 6.2):
6.3.3.1 Construction of the Lower Level Fuzzy System

Generation of fuzzy rules is usually conducted using two steps: fuzzy partition and rule-mapping. Since five variables were used for antecedent parts, direct fuzzy partition was restricted. To solve this problem, the overall geometric effect, with those five antecedent variables, was produced by a fuzzy aggregation method. A fuzzy weighted average was used to produce aggregated geometric effects (Eq. 6.3). As mentioned previously, fuzzy membership functions and fuzzy weights for each of the geometric factors were constructed, and they were used to calculate a fuzzy weighted average for all combinations of the five variables. Then the fuzzy partition and mapping were conducted using this aggregated overall geometric condition. The calculated fuzzy weighted average ranged from 0 to 1. These fuzzy weighted averages for 108 combinations were partitioned within four groups. Using these combinations of five variables whose fuzzy weighted average values were included in each group, a fuzzy rule-mapping procedure was conducted. Through these two procedures, 108 fuzzy rules were created. The FGI, which is the output of the lower level fuzzy system and one of the input variables of the upper level fuzzy system, is classified into four classes designated by the linguistic terms: “good,” “fair,” “poor,” and “very poor.”

\[
COA(A) = \int \frac{u_{j}(x) \cdot x}{u_{j}(x)} \, dx \quad \text{Eq. 6.2}
\]

\[
Overall \ Geometric \ Effect_{j} = \frac{\sum_{k=1}^{5} (w_{k} \otimes A_{jk})}{\sum_{k=1}^{5} w_{k}} \quad \text{Eq. 6.3}
\]

where

\[
Overall \ Geometric \ Effect_{j} = \text{the aggregated geometric effect of a combination } j,
\]
$j$ = each combination with five variables ($j = 1, 2, 3, \ldots, 108$),

$k$ = each geometric factor including median width, horizontal curvature, operating speed, median cross slope, and shoulder width,

$w_k$ = the normalized fuzzy weight of each geometric element ($\sum w_k = 1$),

$A_{jk}$ = the fuzzy membership function representing how significantly $k$\textsuperscript{th} geometric factor influences on median safety in the $j$\textsuperscript{th} combination, and

$\sum_{k=1}^{5}$ and $\otimes$ = fuzzy operations using $\alpha$ – cut interval analysis.

### 6.3.3.2 Construction of the Upper Level Fuzzy Inference System

In the upper level fuzzy system, two antecedent variables were used: FGI and ADT. The FGI from the lower level fuzzy system was used to describe the geometric conditions in terms of the degree of safety, and ADT was used to illustrate traffic flow. Generation of fuzzy rules for the upper level fuzzy system was conducted through direct fuzzy partitioning and rule-mapping with the overall geometric condition and traffic flow condition. The final output representing median safety was named the Fuzzy Median Safety Index (FMSI), which had a range from 0 to 1. Since there was no reference to determine fuzzy membership functions of the consequent variable, FMSI, the value of FMSI was categorized into three classes: “good,” “fair,” “poor,” and “very poor,” which are the most common linguistic terms used to classify the “degree of truth” of the consequent. Preliminarily, a set of fuzzy membership functions for the consequent part was created as symmetric forms. Then they were shifted slightly to better illustrate the Pennsylvania CMC database. High FMSI indicates a safety deficiency regarding median crashes and a greater possibility of a median crash. Figure 6-5 shows the structure of the final fuzzy system.
Antecedent part (if part)

Traffic Flow Condition (ADT)  

Geometric Condition (FGI)  

Consequent (then part) – Fuzzy Median Safety Index

If {Traffic flow condition is _______} and {Fuzzy Geometric Index is _______},  
then {Fuzzy Median Safety Index is ________}

Fuzzy Rules

<table>
<thead>
<tr>
<th>Fuzzy Inference System</th>
<th>Fuzzy Geometric Index</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Good</td>
</tr>
<tr>
<td>Low</td>
<td>Good</td>
</tr>
<tr>
<td>Medium</td>
<td>Good</td>
</tr>
<tr>
<td>High</td>
<td>Fair</td>
</tr>
<tr>
<td>V. High</td>
<td>Fair</td>
</tr>
</tbody>
</table>

Figure 6-5: The Upper Level Fuzzy Logic Representing Median Safety.
6.4 Application of Proposed the Hierarchical Fuzzy Inference System

The results of the developed HFIS were compared with observed crash data for the purpose of validation. For this application, the Pennsylvania median safety database was used per the previous discussion. This database included various elements, such as crash type, severity, and roadway inventory data. Out of those data, the number of CMC crashes and the inventory data of the six variables used in the fuzzy inference system described above were applied. Five years of data on traffic volumes (ADTs) and the geometric features covered by the five variables discussed above for 12,781 roadway segments were used as input values for the lower level or the upper level fuzzy inference system. However, since the safety database did not include an operating speed but posted speed, posted speed was used as a surrogate input variable in place of operating speed. Through the developed HFIS and a defuzzification procedure, FMSIs for each roadway segment were produced and compared with the observed median crash data of the same roadway segments.

First, the relationship between ADT and FGI of the given roadway segments was examined. Through this procedure, the fuzzy partition and rule mapping conducted for the upper level fuzzy inference system were verified. Figure 6-6 shows the relationship between ADT and FGI for the given roadway segments with both CMC crash data and non-crash data. The data for the roadway segments reflect the results of the partition and rule-mapping relatively well. Most of the roadway segments FGI ranged from 0.3 to 0.7 and their ADTs vary widely. The minimum ADT is 481 and maximum ADT is 84,939 vehicles per day. However, most (84.6 percent) of the roadway segments have less than 20,000 ADT. Therefore, most of the given roadway segments have relatively acceptable geometric conditions and uncongested traffic flow conditions.
Then, the FMSIs for 12,781 roadway segments were compared with the number of CMC crashes for the same roadway segments. For instance, a roadway segment in the median safety database has a median width of 68 feet, a 55 mph speed limit, a horizontally curved alignment, is steeper than 6:1 on the median cross slope, and has an ADT of 59,070. The calculated FMSI through the developed HFIS is 0.876. In this roadway segment, 3 CMC crashes per year and 0.002 CMC crash rate per 100 million vehicles were recorded in the median safety database. Figure 6-7 shows the number of CMCs per year against FMSI. CMC crashes fell within a wide range of FMSI from 0.09 to 0.91. Many CMC crashes happened at roadway segments with an FMSI between 0.3 and 0.5 rather than at roadway segments with higher FMSI values. However, these interpretations of the results with only the number of CMC crashes for each FMSI can draw a biased conclusion because a CMC crash is a rare type of median crash and 94 percent of the roadway segments (whether or not CMC crashes occurred within that section) were less than 0.5 FMSI. In the database, CMC crashes were recorded for only one percent of the roadway segments (130 of 12781). Therefore, the rate or mean of

Figure 6-6: ADT and Fuzzy Geometric Index.
CMC crash frequency, considering the number of data for each FMSI bin, should be investigated. Meanwhile, the wide range of FMSI with CMC crashes shows that crashes can occur even on road segments with relatively good driving conditions. As such, there are other factors influencing median safety other than those reflecting the physical driving environment as used in this study. For example, factors regarding drivers’ physical or mental condition and weather can influence median safety. Figure 6-8 shows the mean of CMC crash frequency and CMC crash rate per 100 million vehicles versus FMSI. As shown in Figure 6-8(a), the mean of CMC frequency increases exponentially with an increase of FMSI. Typically, a roadway segment with an FMSI equal to or greater than 0.7 included more CMC crashes than those segments with an FMSI less than 0.7. This trend is also shown in the mean of CMC crash rate as shown in Figure 6-8(b). The rate of increase of this mean value enlarges suddenly at FMSI values greater than 0.7. Since the given roadway segments were higher quality roadways (i.e., Interstate highways or expressways) there were small amounts of data for relatively high FMSI values (see the percentage of the number of data for each bin in Figure 6-8(b)).

There were many other median safety factors that were not used in this study due to the limited availability of data, such as weather, radius of horizontal curves, and factors regarding drivers. However, the proposed HFIS can produce an indicator, FMSI, which explains well the degree of median safety on Interstate highways or expressways. It is one of the advantages of the fuzzy approach to analyze or infer well with ambiguous or incomplete information. Therefore, it can be concluded that the proposed HFIS, in terms of FMSI values, reflect well the real median crash problem, and the incorporated transportation expert opinions appear to be valid.
Figure 6-7: Fuzzy Median Safety Index & CMC Frequency
Figure 6-8: The Crossover Median Crash and Fuzzy Median Safety Index

Note: The numbers in the parenthesis indicate the percentage of the number of data for each bin.
6.5 Conclusion

In this paper, a new approach to incorporate transportation experts’ opinions using the HFIS was developed. Generally, transportation experts use linguistic information and their own subjective decision criteria to formulate and express their opinion. However, it is difficult to aggregate those linguistic and subjective experts’ opinions using conventional methods. The proposed method allows for the analysis and aggregation of the subjective and linguistic expert opinions taking into consideration the unique characteristics and decision criteria of an individual expert.

To apply this method, variables in the HFIS were selected through the transportation expert survey results of a previous study. The fuzzy membership functions for the selected six variables were constructed using common engineering knowledge garnered from a review of the experts’ opinions, a review of the references related to transportation safety, and the authors’ own knowledge. A hierarchical structure for the fuzzy system was applied to reduce the complexity of a multivariable fuzzy system, which can lead to the fuzzy rule explosion problem. The fuzzy weighted average method was used in the process of formulating the fuzzy inference system to avoid the difficulty of fuzzy rule mapping with a large number of variables. The incorporated experts’ opinions regarding median safety were finally expressed by FMSI as an indicator of the degree of median safety. Then, the values of FMSI computed using roadway inventory data were compared with observed median crashes to validate the fuzzy results. Since the roadway type used in this study was the Interstate highway and expressway, most of roadway segments in the database have relatively favorable driving conditions. For this reason, most of the roadway segments were less than 0.5 FMSI. To avoid a biased interpretation of the results from the unbalanced data, the mean of CMC crash frequency and the CMC crash rate were used for the validation process. The mean of CMC frequency increases exponentially with an increase of FMSI. Typically, a roadway segment with an FMSI equal to or greater than 0.7 included more CMC crashes than those segments with an FMSI less than 0.7. Through these comparisons, the developed
HFIS based on experts’ opinions was evaluated as the system that can explain relatively well the degree of median safety for Interstate highways and expressways.

This study is the first endeavor to incorporate transportation experts’ opinions and the first to evaluate median safety of Interstate highways and expressways using fuzzy techniques. Therefore, some of the methods developed herein need to be further refined in this application, especially in the processes of selecting variables and constructing fuzzy membership functions for the variables. For example, horizontal curvature influences median safety primarily by different horizontal design elements rather than just the presence of a horizontal curve. However, the available median safety database included information on the presence (or absence) of horizontal curvature not other, more detailed information about the horizontal curves. Given this limitation, the fuzzy membership functions for horizontal curvature had to be developed with just two levels when considering the presence of curves in this study. This problem was also encountered in the construction of fuzzy membership function for median cross slope. It must also be kept in mind that this study applied only to Pennsylvania Interstate highways and expressways. Therefore, as a follow on to the present work, a fuzzy inference system should be developed as more of a universal system, one which also can be applied for other states’ Interstate highways and expressways and can cover all (or, at least, more) types of roadway. Generally, the basic concepts and procedures developed herein are able to be used for other transportation problems related to human perception, for example, analysis of peoples’ opinions regarding congestion or service quality, which would be done through the further study.
CHAPTER 7

VALIDATION OF THE FUZZY ANALYSIS RESULTS

7.1 Introduction

In an engineering research process, one of the critical procedures is to test if the developed models, systems, or methodologies work appropriately and produce outputs comparable to the real situations. This procedure is known as model validation. Generally, the validation process is based on the assumption that there is a real or true value of the modeled output. For example, traffic volumes estimated through a simulation program are tested using traffic volumes measured on roadways. A validation process is one of the most difficult processes in studies related to human factors or perceptions because of their “ambiguity” and “variety.” To directly validate an opinion, idea, or concept perceived by one person or a group of people is extremely difficult. This is because the true “values” of the individual perceptions to be validated are difficult to identify and aggregate. An alternative way to approach this problem is to test the subjects’ perceptions indirectly using surrogates that can be easily measured. For example, after evaluating drivers’ perceptions regarding the degree of highway safety, this degree of safety perception can be compared to the observed crash data as a surrogate to test whether the evaluated perception corresponds with the real likelihood of a crash.

In this chapter, two preliminary methods of validating fuzzy results, i.e. direct validation and indirect validation, are described. Also, the application of these two validation methods is conducted using transportation user perception regarding the service quality of signalized intersections and the degree of safety when driving adjacent to medians. Through these applications, the proposed fuzzy approaches for analyzing transportation user perception can be used to support the point that the fuzzy approach is better than other more conventional methods. To apply the direct validation method, an experimental study involving the evaluation of the service quality of signalized
intersections was conducted. The application of the indirect validation method was performed based on a review of the observed cross over median collision (CMC) data.

7.2 Two Validation Methods for Transportation User Perception

In this study, two prospective validation methods are proposed for use in a transportation user perception study. The first method employs direct user responses gathered through surveys or experiments. The second method uses surrogates of transportation user perception. The former is called a “direct validation,” and the latter is called an “indirect validation” in this study.

7.2.1 Direct Validation Method

The true values of particular individual perceptions are difficult to identify and aggregate. Usually, the individual’s perceptions are differentiated by the characteristics of individual evaluators and the situational characteristics when they are perceived. However, if the perceptions evaluated by the individuals can be obtained, they can be regarded as true values by the evaluators and compared with the perceptions estimated by the fuzzy techniques for a validation process. In other words, if a subject is asked to evaluate the overall perception of a particular transportation system and to evaluate simultaneously specific perceptions based on certain criteria, the overall perception can be used as a true value of the subject’s opinion. This value can be compared with the estimated fuzzy output based on the aforementioned criteria. For example, the survey conducted by Rao and his colleagues (1998) included both the overall and specific perceptions regarding technical support service quality as shown in the following Figure 7-1:
In this case, answers from the last question regarding the perception of the quality of the service can be used as the overall perception or the true value. The answers to the question regarding the seven factors can be used to estimate perception using the fuzzy aggregation method. The results from the fuzzy aggregation process can be compared with this overall perception regarding the quality of the technical support service.

In this validation method, the total sum of the difference between the true values and the fuzzy outputs (\( \text{Sum of Difference}_F \)) is compared with the total sum of the difference between the true values and the results from a conventional method (\( \text{Sum of Difference}_C \)). The true perception value, \( TP_i \), is the overall perception evaluated by an individual subject \( i \). The perception estimated by the fuzzy aggregation, such as a fuzzy weighted average, is denoted \( FP_i \), while the perception being estimated by the conventional method is denoted \( CP_i \). These two sums of difference are as following equations (Eq. 7.1 and Eq. 7.2):

![Figure 7-1: Illustration of the survey to evaluate technical support service quality (Rao et al. 1998)](image)
If the “Sum of Difference\(_F\)” is smaller than “Sum of Difference\(_c\)”, it can be concluded that the results from the fuzzy applications give a better evaluation of the real individual perception than the results from the conventional method. In the application of this direct validation method, perception regarding the service quality of signalized intersection was used. A more detailed explanation of the application of this method will be provided in section 7.3.

### 7.2.2 Indirect Validation Method

To overcome the difficulties of directly testing the fuzzy results of human perception, surrogates of the true human perception can be used. Indirect validation is conducted by comparing fuzzy results with surrogates of a particular perception. For example, the observed crash rate can be used instead of drivers’ perceptions regarding the degree of highway safety.

The degree of safety that drivers perceive in the field has a close relationship to observed crash rates. As mentioned in the chapter 6, when the fuzzy results regarding median safety, namely as FMSI, increased, the observed CMC crash rates also increased. Indeed there are many studies that measured various driver perceptions in an indirect way. Kita measured drivers’ utility representing the degree of drivers’ satisfaction by analysis of driving behavior as the revealed preferences (Kita 2000). Hamad and Kikuchi (2002) measured a traffic congestion index using the fuzzy inference approach and compared the results with level of service as determined by the *Highway Capacity Manual*.

\[
Sum of Difference\(_F\) = \sum_{i=1}^{n} (|TP_i - FP_i|) \quad \text{Eq. 7.1}
\]

\[
Sum of Difference\(_c\) = \sum_{i=1}^{n} (|TP_i - CP_i|) \quad \text{Eq. 7.2}
\]
7.3 Direct Validation of Fuzzy Transportation User Perception

7.3.1 Introduction

In this section, the proposed direct validation method is applied using the perception of the service quality of signalized intersections. Two perceptions regarding the service quality of signalized intersections were evaluated, for the purposes of this application, through an experiment. The first perception that the individual subjects “evaluated” was the overall service quality of several different signalized intersections. It was a general opinion about what the subjects perceive while traversing the intersection. This “measure” of overall service quality of the signalized intersection was used as a true value in the validation process. The second perception was an amalgam of the specific service quality subjects experienced relative to certain service-related criteria. It was aggregated using a fuzzy aggregation method and a conventional method. The aggregated perceptions were compared with the “true” perception values.

7.3.2 Experimental Design

An experiment was designed to evaluate the individual perception regarding the service qualities of signalized intersections using video data. In the experiment video scenes, previously recorded in the Altoona and Tyrone areas in Pennsylvania, were used (Pecheux 2000). Pecheux conducted the experiment to test subjects’ delay-estimating capabilities and level of service (LOS) perceptions. Video scenes were taken from the driver’s vantage point to capture a view of the entire intersection and the facilities around the intersection. Pecheux used 24 scenes of signalized intersections with various traffic conditions and types of signalization (i.e., actuated and fixed time signal operation). Each scene included a driver approaching at red traffic signal, waiting for the signal to turn green, and proceeding through the intersection. In her experimental study, subjects were asked to estimate the time spent stopped at the traffic signal and to rate the service
quality of the signalized intersection on a scale of 1 to 10, where “1” represented an unacceptable condition and “10” represented excellent conditions. This all took place while the subjects were watching the video scenes of the intersection approaches.

Twelve signalized intersections out of Pecheux’s 24 intersections were selected to be used for a review of the traffic conditions and types of signalization at each intersection. Table 7-1 shows the selected signalized intersections and their conditions.

---

Table 7-1: Selected Signalized Intersections, their Traffic Conditions and the Rates of Service Quality.

<table>
<thead>
<tr>
<th>Intersection ID</th>
<th>Type of Signalization</th>
<th>LOS</th>
<th>Measured Delay (min.)</th>
<th>Rates of Service Quality (1 to 10)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Min.</td>
</tr>
<tr>
<td>1</td>
<td>FT_MA</td>
<td>A</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>3</td>
<td>FT_MA</td>
<td>C</td>
<td>23</td>
<td>1</td>
</tr>
<tr>
<td>5</td>
<td>FT_MA</td>
<td>E</td>
<td>62</td>
<td>1</td>
</tr>
<tr>
<td>7</td>
<td>FT_MS</td>
<td>A</td>
<td>6</td>
<td>1</td>
</tr>
<tr>
<td>8</td>
<td>FT_MS</td>
<td>B</td>
<td>15</td>
<td>2</td>
</tr>
<tr>
<td>12</td>
<td>FT_MS</td>
<td>F</td>
<td>106</td>
<td>1</td>
</tr>
<tr>
<td>14</td>
<td>A_MA</td>
<td>B</td>
<td>15</td>
<td>3</td>
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<td>16</td>
<td>A_MA</td>
<td>D</td>
<td>35</td>
<td>1</td>
</tr>
<tr>
<td>18</td>
<td>A_MA</td>
<td>F</td>
<td>85</td>
<td>1</td>
</tr>
<tr>
<td>21</td>
<td>A_MS</td>
<td>C</td>
<td>27</td>
<td>2</td>
</tr>
<tr>
<td>22</td>
<td>A_MS</td>
<td>D</td>
<td>28</td>
<td>3</td>
</tr>
<tr>
<td>23</td>
<td>A_MS</td>
<td>E</td>
<td>68</td>
<td>1</td>
</tr>
</tbody>
</table>

- FT_MA : Fixed Time, Major Street
- FT_MS : Fixed Time, Minor Street
- A_MA : Actuated Major Street
- A_MS : Actuated Minor Street

The criteria to be used for this study to evaluate the service quality of the signalized intersections were determined through the results of a literature review. In an early study, Sutaria and Haynes (1977) used five criteria to evaluate LOS at signalized intersections. Pfefer (1999) suggested reflecting the public perception of service quality in planning, designing, and operating highway facilities. He indicated the five criteria
used to determine the public perception of LOS in highway systems. Pecheux et al. (2000) indicated 15 criteria related to the service quality of signalized intersections as identified by survey participants. Pecheux et al. (2004) determined the factors influencing automobile drivers’ perceptions of service quality on urban streets through an in-vehicle field study. Participants indicated the important features on urban streets related to capacity and level of service and ranked them accordingly. Visibility of traffic signs and signals and the timing of traffic signals were the top ranked factors. Zhang (2004) investigated which factors are more important to drivers when they drive through a “large” signalized intersection. Flannery and Pedersen (2005) stated that customers perceive a signalized intersection with long gaps in traffic on the major road as having a poor service quality if they were waiting for a green phase on an adjacent minor road. They also indicated several other factors influencing the service quality. Table 7-2 shows the criteria suggested from several studies.

<table>
<thead>
<tr>
<th>Authors</th>
<th>Transportation System</th>
<th>Factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sutaria and Haynes (1977)</td>
<td>Signalized intersections</td>
<td>• Delay</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Number of stops</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Traffic congestion</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Number of trucks and bus</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Difficulty of lane changing</td>
</tr>
<tr>
<td>Pfefer (1999)</td>
<td>Highway systems</td>
<td>• Mobility</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Safety</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Environment</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Comfort and convenience</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Road-user direct cost</td>
</tr>
</tbody>
</table>
Table 7-2. Criteria Identified from Previous Studies (con’t).

<table>
<thead>
<tr>
<th>Authors</th>
<th>Transportation System</th>
<th>Factors</th>
</tr>
</thead>
</table>
| Pecheux et al. (2000) | Signalized intersections | • Delay  
• Traffic signal efficiency  
• Arrows/lanes for turning vehicles  
• Visibility of traffic signals from queue  
• Clear/legible signs and road markings  
• Geometric design of intersection  
• Leading left-turn phasing scheme  
• Visual clutter-distractions  
• Size of intersection  
• Pavement quality  
• Queue length  
• Traffic mix  
• Location  
• Scenery/aesthetics  
• Presence of pedestrians |
| Pecheux et al. (2004) | Urban Street | • Visibility of signs/signal  
• Timing of traffic signals  
• Ability to maneuver vehicle  
• Left-turn only lanes at intersection  
• Rate of traffic flow or Traffic volume  
• Divided Roadway  
• Overall travel time to destination  
• Pavement quality  
• Consistency/reliability of travel time  
• Number of signalized intersections  
• Aggressive drivers  
• Interaction between vehicles |
Table 7-2. Criteria Identified from Previous Studies (con’t).

<table>
<thead>
<tr>
<th>Authors</th>
<th>Transportation System</th>
<th>Factors</th>
</tr>
</thead>
</table>
| Zhang (2004)             | Signalized intersections       | • Traffic Signal Responsiveness  
• Ability to go through the intersection within one cycle of light changes  
• Availability of left-turn only lanes and protected left-turn signal for vehicles turning left  
• Pavement marking for separating and guiding traffic  
• Availability of a protected left-turn signal for vehicles turning left  
• Pavement quality  
• Availability of left-turn only lanes for vehicles turning left  
• Waiting time  
• Heavy vehicles such as trucks and buses that are waiting ahead  
• Availability of right-turn only lanes for vehicles turning right |
| Aimee and Pedersen (2005)| Signalized intersections       | • Long gaps in traffic on the main road  
• Quality of signing and traffic markings  
• Confusion about what lane to be in  
• Smoothness of pavement  
• Whether they perceive the road as being safe  
• Information about delays  
• Interference from bicycles or pedestrians in the roadway |

Through the review of these references, the following common factors were found:
- Delay (or ability to go through the intersection within one cycle of light changes
- Length of gaps in traffic on the main road while drivers wait for a green phase on a side road
- Efficiency and visibility of traffic signals and traffic signs
- Pavement quality (smoothness or pavement)
- Efficiency and visibility of pavement marking and delineation
- Geometric design of intersection (turning exclusive lane, intersection angle, corner clearance, sight distance)
- Traffic mix
- Presence of pedestrian
- Safety issues

Based on the results of the literature review, six influencing factors were finally selected as criteria for evaluating the perception of service quality of signalized intersections. Table 7-3 shows the final six criteria and their descriptions.
The survey questions were designed to satisfy with four different objectives, and they consist of five parts. The four objectives and five parts of the survey questions are as follows:

- Evaluate overall service quality of signalized intersections with linguistic and numerical values (Part 1 and 5)
- Determine relative importance (i.e. weight) of six criteria using pair-wise comparisons (Part 2)
- Determine thresholds for five linguistic ordered scales (Part 3)
- Evaluate the specific service quality of signalized intersections based on the six criteria using five linguistic ordered scales (Part 4)

The numerical service qualities of signalized intersections that subjects determined and answered in the part 5 of the survey are used for validation as a representative true value.

---

Table 7-3: The Six Criteria Selected for Inclusion in this Study and Their Descriptions.

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Traffic Signal Waiting time (SWT)</td>
<td>Whether the waiting time due to the signal is tolerable or not.</td>
</tr>
<tr>
<td>Length of Gaps in Traffic on the Cross-Street (GAP)</td>
<td>Whether the length of gaps in traffic on the cross street while drivers wait for a green indication on their road is tolerable or not.</td>
</tr>
<tr>
<td>Traffic Signal Operation (TSO)</td>
<td>Whether the traffic signals operate efficiently or not.</td>
</tr>
<tr>
<td>Traffic Signal Visibility (TSV)</td>
<td>Whether the traffic signals are clearly visible or not.</td>
</tr>
<tr>
<td>Information Guidance Systems (IGS)</td>
<td>Whether the intersection guidance information functions well or not. (traffic signs, road markings, or other delineation devices)</td>
</tr>
<tr>
<td>Physical Features of the Intersection (PFI)</td>
<td>Whether the physical features of the intersection are good or not. (turning exclusive lane, intersection angle, corner clearance, sight distance)</td>
</tr>
</tbody>
</table>
of the individual perception regarding the service quality. The accuracy of the responses to questions in the part 5 seems to dominate the results of this validation. To increase the accuracy, the questions used to evaluate the overall service quality were asked twice, once at the beginning of the experiment (part 1) and once at the end of the experiment (part 5). In other words, the first part of the experiment is a practice or training step for part 5, the last part. There were two parts of the experiment used to construct fuzzy membership functions. Questions in part 2 were designed to create fuzzy weights for each of the six criteria using the Saaty’s pair-wise comparison method. Questions in the part 3 were designed to construct fuzzy membership functions representing the five linguistic ordered scales using the interval estimation method. Questions in part 4 were designed to evaluate the service quality of signalized intersections using five linguistic ordered scales. These survey questions were the most common type used to investigate the quality of a certain perception, such as, the users’ satisfaction of the transportation system or the degree of safety perceived by users. All of the questions used in the five parts are included in Appendix D.

An advertisement was placed in a local daily newspaper and a local college newspaper to recruit subjects for participation. Because of cost and scheduling limitations related to the study, only 30 subjects were enrolled in the experiment. Twenty-seven out of the 30 subjects completed all of the questions, and those 27 responses were used for the analyses. Twenty-seven responses are not enough to conclusively validate the results of the fuzzy applications; however, their responses were enough to testify if fuzzy application work appropriately and the fuzzy results comply with the real situations as a frontier study. Table 7-4 shows a demographic summary of the 27 participants.
Table 7-4: Demographic Summary of the Participants.

<table>
<thead>
<tr>
<th></th>
<th>Younger driver (Under 25 yr.)</th>
<th>Middle aged driver (25 ~ 60)</th>
<th>Older driver (Over 60yr.)</th>
<th>Sum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>1</td>
<td>6</td>
<td>6</td>
<td>13</td>
</tr>
<tr>
<td>Female</td>
<td>2</td>
<td>7</td>
<td>5</td>
<td>14</td>
</tr>
<tr>
<td>Sum</td>
<td>3</td>
<td>13</td>
<td>11</td>
<td>27</td>
</tr>
</tbody>
</table>

7.3.3 Application of the Direct Validation

7.3.3.1 Descriptive Summary of Survey Results

Based on the survey responses from part 2, the subject data yielded a pair-wise comparison among the six criteria. Using these results, the relative importance of the six criteria that each subject judged was estimated through the Saaty’s eigenvector method. Figure 7-2 shows the mean of the ordered rankings for the relative importance of the selected criteria by using the sets of the calculated weights, where “1” represented the most important criterion and “6” represented the least important criterion.
The information from part 3 provided the thresholds for each of the five linguistic ordered scales, including the following: strongly disagree, disagree, neither disagree nor agree, agree, and strongly agree. The five figures in Figure 7-3 show the relative frequency of each threshold. The range of agreement for the “strongly disagree” linguistic scale is 0 to 35. The highest likelihood of agreement for this linguistic scale ranges from 0 to 10. In the next scale, (i.e., disagree) the range of agreement is 5 to 60. The highest likelihood of agreement for this linguistic scale ranges from 20 to 30. The participants’ threshold values for “neither disagree nor agree” seem to be skewed to the low agreement side. The range of agreement for this linguistic scale is 25 to 75. The highest likelihood agreement for this linguistic scale ranges from 45 to 55. In case of the “agree” scale, the threshold ranges from 45 to 95 and the highest likelihood threshold ranges from 70 to 80. The range of the last scale (i.e., strongly agree) is 60 to 100 with the highest likelihood threshold ranging from 95 to 100.
a) Strongly Disagree

b) Disagree

Figure 7-3: The Relative Frequency of Thresholds for Each Five Linguistic Ordered Scales.
c) Neither Disagree nor Agree

![Graph showing the relative frequency of thresholds for each five linguistic ordered scales.]

d) Agree

![Graph showing the relative frequency of thresholds for each five linguistic ordered scales.]

Figure 7-3: The Relative Frequency of Thresholds for Each Five Linguistic Ordered Scales (con’t).
The evaluation of the specific service quality of signalized intersections based on the six criteria was processed using the responses from part 4 of the experiment. In this evaluation, five linguistic ordered scales, for which the thresholds were investigated in the part 3 experiment, were used. Table 7-5 shows the mean values of the responses regarding service quality. For intersection 5, the participants were satisfied with the service quality of the intersection for all criteria based on the fact that the mean rankings for all criteria were over 3.5. In contrast, participants were unsatisfied with the service quality of intersection 12 for most criteria except for traffic signal visibility.
The last part of the experiment dealt with the overall service quality of signalized intersections. Questions in this part consisted of two sections, linguistic evaluation and numerical evaluation. The statements for linguistic evaluation are poor, acceptable, and good. Cross relationships between the results of the linguistic evaluation and the numerical evaluation vary by the participant. For example, 17 participants responded that the service quality of intersection 1 is poor. Out of the 17 participants, participant #10 answered 10 for the degree of satisfaction while participant #21 answered 70 for the degree of satisfaction. Twelve out of the 17 participants answered between 30 and 40. Based on the results shown in Table 7-6, the overall service qualities for intersection 5 and 22 are relatively high while the overall service qualities for intersection 1 and 12 are relatively low.

### Table 7-5: Specific Service Quality of Signalized Intersections based on the Six Criteria.

<table>
<thead>
<tr>
<th>Intersection ID</th>
<th>SWT</th>
<th>GAP</th>
<th>TSO</th>
<th>TSV</th>
<th>IGS</th>
<th>PFI</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4.30</td>
<td>3.96</td>
<td>2.44</td>
<td>2.59</td>
<td>2.78</td>
<td>3.22</td>
</tr>
<tr>
<td>3</td>
<td>2.89</td>
<td>3.30</td>
<td>3.74</td>
<td>4.15</td>
<td>3.30</td>
<td>3.44</td>
</tr>
<tr>
<td>5</td>
<td>4.11</td>
<td>3.59</td>
<td>3.85</td>
<td>3.59</td>
<td>3.52</td>
<td>3.78</td>
</tr>
<tr>
<td>7</td>
<td>2.78</td>
<td>3.48</td>
<td>3.59</td>
<td>3.78</td>
<td>2.93</td>
<td>2.59</td>
</tr>
<tr>
<td>8</td>
<td>3.26</td>
<td>2.59</td>
<td>3.59</td>
<td>3.85</td>
<td>2.81</td>
<td>2.78</td>
</tr>
<tr>
<td>12</td>
<td>1.70</td>
<td>2.04</td>
<td>3.07</td>
<td>3.56</td>
<td>2.33</td>
<td>2.48</td>
</tr>
<tr>
<td>14</td>
<td>3.93</td>
<td>3.22</td>
<td>3.74</td>
<td>4.07</td>
<td>3.22</td>
<td>3.30</td>
</tr>
<tr>
<td>16</td>
<td>3.26</td>
<td>2.96</td>
<td>3.26</td>
<td>2.85</td>
<td>2.52</td>
<td>2.56</td>
</tr>
<tr>
<td>18</td>
<td>3.96</td>
<td>3.41</td>
<td>3.74</td>
<td>4.04</td>
<td>2.63</td>
<td>2.63</td>
</tr>
<tr>
<td>21</td>
<td>3.11</td>
<td>3.26</td>
<td>3.67</td>
<td>2.81</td>
<td>2.96</td>
<td>3.11</td>
</tr>
<tr>
<td>22</td>
<td>3.74</td>
<td>3.37</td>
<td>3.85</td>
<td>3.48</td>
<td>3.63</td>
<td>3.74</td>
</tr>
<tr>
<td>23</td>
<td>2.22</td>
<td>3.07</td>
<td>3.85</td>
<td>4.07</td>
<td>3.63</td>
<td>3.44</td>
</tr>
</tbody>
</table>

Note: 1 represents “Strongly disagree” and 5 represents “Strongly agree."
7.3.3.2 Evaluation of the Service Quality of Signalized Intersection

The perception regarding the service quality of signalized intersections, as reported by the individual subjects, was estimated using a fuzzy aggregation method. This process follows the process for evaluating driver perception of VMS, as explained in chapter 5.

Prior to aggregating the individual perception, two categories of fuzzy membership functions were constructed. These included the fuzzy membership functions of the five linguistic statement scales and the relative importance of the weight of the six criteria. The first set of fuzzy membership functions, which represent the five scales of linguistic statements, were created from the survey using interval estimation (questions in part 3). A trapezoidal fuzzy membership function was used, and its four parameters \((a, b, c, d)\) were determined based on the relative frequency of the responses. Figure 7-4 shows the first set of the constructed fuzzy membership functions. The second set of fuzzy membership functions, the fuzzy weights of the six criteria, was constructed using

<table>
<thead>
<tr>
<th>Intersection ID</th>
<th>Total Number</th>
<th>Numbers of Response</th>
<th>Mean of Numerical Satisfaction</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>27</td>
<td>17 8 2</td>
<td>40.81</td>
</tr>
<tr>
<td>3</td>
<td>27</td>
<td>2 21 4</td>
<td>56.81</td>
</tr>
<tr>
<td>5</td>
<td>27</td>
<td>0 18 9</td>
<td>65.44</td>
</tr>
<tr>
<td>7</td>
<td>27</td>
<td>9 15 3</td>
<td>47.96</td>
</tr>
<tr>
<td>8</td>
<td>27</td>
<td>5 17 5</td>
<td>55.52</td>
</tr>
<tr>
<td>12</td>
<td>27</td>
<td>17 9 1</td>
<td>35.74</td>
</tr>
<tr>
<td>14</td>
<td>27</td>
<td>4 13 10</td>
<td>61.67</td>
</tr>
<tr>
<td>16</td>
<td>27</td>
<td>8 18 1</td>
<td>47.78</td>
</tr>
<tr>
<td>18</td>
<td>27</td>
<td>3 19 5</td>
<td>59.63</td>
</tr>
<tr>
<td>21</td>
<td>27</td>
<td>8 14 5</td>
<td>52.22</td>
</tr>
<tr>
<td>22</td>
<td>27</td>
<td>0 16 11</td>
<td>66.41</td>
</tr>
<tr>
<td>23</td>
<td>27</td>
<td>7 16 4</td>
<td>50.85</td>
</tr>
</tbody>
</table>

Table 7-6: Overall Service Quality of the Signalized Intersections
Saaty’s eigenvector method. The triangular fuzzy membership function was selected for use. Its three parameters \((a, b, c)\) were determined based on minimum, medium, and maximum values of weights as calculated using Saaty’s eigenvector method. The type of fuzzy membership functions (Section 2.2.4) and Saaty’s eigenvector method (Section 4.3.2) were explained in greater detail in previous sections. Figure 7-5 shows the second sets of the fuzzy membership functions constructed using Saaty’s eigenvector method.

![Figure 7-5: Fuzzy Membership Functions of Five Scales Linguistic Statement.](image)
Using the constructed fuzzy membership functions, the specific perceptions of service quality based on each criterion were aggregated to represent the individual perception. The individual perception regarding the service quality of the signalized intersection was computed by applying the fuzzy weighted average as shown in the following equation (Eq. 7.3):

\[ a = 0.016 \\
b = 0.049 \\
c = 0.079 \]

\[ a = 0.019 \\
b = 0.034 \\
c = 0.172 \]

\[ a = 0.030 \\
b = 0.246 \\
c = 0.485 \]

\[ a = 0.022 \\
b = 0.303 \\
c = 0.511 \]

\[ a = 0.050 \\
b = 0.188 \\
c = 0.400 \]

\[ a = 0.023 \\
b = 0.097 \\
c = 0.320 \]

Figure 7-5: Fuzzy Weights of Six Criteria.
\[ FP_{ij} = \frac{\sum_{k=1}^{6} (w_k \otimes SQ_{jk})}{\sum_{k=1}^{6} w_k} \]  
\text{Eq. 7.3}

where

\( FP_{ij} \) = the service quality of the \( i^{th} \) intersection perceived by participant \( j \) using the fuzzy weighted average \( (j=1, 2, 3\ldots 27) \),

\( k \) = the criterion for evaluating the service quality of signalized intersections including SWT, GAP, TSO, TSV, IGS, and PFI,

\( w_k \) = the normalized fuzzy weight of the six criteria \( (\sum w_k = 1) \),

\( SQ_{jk} \) = the fuzzy number representing the individual response of the service quality of the signalized intersection regarding criteria \( k \), and

\[ \sum_{k=1}^{6} \] and \( \otimes \) = fuzzy operations using \( \alpha \)-cut interval analysis.

The 27 individual perceptions regarding the service quality of signalized intersections were estimated and compared with the results from the conventional weighted average method. Since the estimated individual perceptions were fuzzy numbers, they were transformed into crisp numbers using the Center-of-Area defuzzification method. This allows for an easier comparison. Figure 7-6 shows an example of the defuzzified individual perceptions regarding the service quality of intersection 1.
Then, the service qualities were estimated using a conventional method. To produce the outputs for comparison with the fuzzy output, a simple weighted average was calculated using follows (Eq. 7.4):

\[
CP_{ij} = \frac{\sum_{k=1}^{6} (w_k \times SQ_{jk})}{\sum_{k=1}^{6} w_k}
\]

where

- \( CP_{ij} \) = the service quality of the \( i \)th intersection evaluated by subject \( j \) using a simple weighted average \( (j = 1,2,3 \ldots 27) \),
- \( k \) = the criterion for evaluating the service quality of signalized intersections including SWT, GAP, TSO, TSV, IGS, and PFI,
- \( w_k \) = the normalized weight of the six criteria \( (\sum w_k = 1) \),
- \( SQ_{jk} \) = the responses from subject \( j \) regarding service quality based on criterion \( k \) using the five linguistic scales.

Figure 7-6: Service Quality of Intersection 1 Using the Fuzzy Weighted Average.
For the purpose of comparison with the fuzzy output, each of the five linguistic ordered scales were converted to numerical degrees of agreement ranging 0 to 100. In the survey questions in part 3, subjects were asked to indicate their thresholds of the five linguistic scales using interval estimation. To calculate the conventional weighted average, the middle value of the interval that subjects indicated was used as the converted degrees of agreement. Table 7-7 shows the converted degrees of agreement of the five linguistic scales.

Table 7-7: Converted Degrees of Agreement for the Five Linguistic Scales.

<table>
<thead>
<tr>
<th>Five linguistic scales</th>
<th>Middle value of the interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strongly Disagree</td>
<td>5</td>
</tr>
<tr>
<td>Disagree</td>
<td>25</td>
</tr>
<tr>
<td>Neither disagree nor agree</td>
<td>50</td>
</tr>
<tr>
<td>Agree</td>
<td>75</td>
</tr>
<tr>
<td>Strongly Agree</td>
<td>95</td>
</tr>
</tbody>
</table>

The means of the weights (non-fuzzy values) estimated using Saaty’s eigenvector method were used to calculate the conventional weighted averages. Table 7-8 shows the weights of the six criteria.

Table 7-8: Weights of the Six Criteria.

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Traffic Signal Waiting Time (SWT)</td>
<td>0.063</td>
</tr>
<tr>
<td>Unused Traffic Gap on the cross street (GAP)</td>
<td>0.064</td>
</tr>
<tr>
<td>Traffic Signal Operation (TSO)</td>
<td>0.235</td>
</tr>
<tr>
<td>Traffic Signal Visibility (TSV)</td>
<td>0.295</td>
</tr>
<tr>
<td>Information Guidance System (IGS)</td>
<td>0.223</td>
</tr>
<tr>
<td>Physical Features of Intersection (PFI)</td>
<td>0.120</td>
</tr>
</tbody>
</table>
Figure 7-7 shows the individual perceptions regarding the service quality of intersection 1 based on the concept of the conventional weighted average.

![Figure 7-7: Service Quality of Intersection 1 using on the Conventional Weighted Average.](image)

### 7.3.4 Validation Results

Using equations 7_1 and 7_2, the sum of the absolute differences between the responded service quality and the service qualities estimated by the conventional weighted average as well as by the fuzzy weighted average were calculated. Then the two sums of the absolute differences were compared to each other. Table 7-9 and Figure 7-8 show the results of the comparison. A higher value of the absolute difference means the estimated perception is a weaker precursor of the observed service quality, which is regarded as “a true value of service quality as perceived by drivers,” while a lower value means the estimated perception is a stronger precursor of the observed service quality.
Table 7-9: Comparison of Outputs from the Fuzzy Application with Outputs from the Conventional Method.

<table>
<thead>
<tr>
<th>Intersection</th>
<th>Absolute Difference</th>
<th>From Conventional method</th>
<th>From Fuzzy Application</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Sum</td>
<td>Mean</td>
</tr>
<tr>
<td>1</td>
<td></td>
<td>411.130</td>
<td>15.227</td>
</tr>
<tr>
<td>3</td>
<td></td>
<td>388.668</td>
<td>14.395</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td>362.025</td>
<td>13.408</td>
</tr>
<tr>
<td>7</td>
<td></td>
<td>465.704</td>
<td>17.248</td>
</tr>
<tr>
<td>8</td>
<td></td>
<td>359.441</td>
<td>13.313</td>
</tr>
<tr>
<td>12</td>
<td></td>
<td>558.284</td>
<td>20.677</td>
</tr>
<tr>
<td>14</td>
<td></td>
<td>402.866</td>
<td>14.921</td>
</tr>
<tr>
<td>16</td>
<td></td>
<td>485.064</td>
<td>17.965</td>
</tr>
<tr>
<td>18</td>
<td></td>
<td>352.625</td>
<td>13.060</td>
</tr>
<tr>
<td>21</td>
<td></td>
<td>420.353</td>
<td>15.569</td>
</tr>
<tr>
<td>22</td>
<td></td>
<td>386.369</td>
<td>14.310</td>
</tr>
<tr>
<td>23</td>
<td></td>
<td>615.342</td>
<td>22.790</td>
</tr>
</tbody>
</table>

Figure 7-8: Comparison of the Sum of the Absolute Difference of the Service Quality of the Signalized Intersections.
For most of the intersections, except for intersections 14 and 18, the perceptions regarding the service quality of signalized intersections estimated by a fuzzy weighted average are closer to the observed perceptions of the subjects than the service quality estimated by a conventional weighted average as shown in Table 7-9 and Figure 7-8. Based on this finding, it can be concluded that the perception regarding the service quality of signalized intersections evaluated using the fuzzy weighted average is in greater agreement with the actual perception that people perceive in the field than the service quality evaluated using the conventional method.

However, the service qualities estimated using the two different methods are not noticeably different. The likely reason for the small difference between the two is that the estimations were made by following the similar procedures using the same input data, such as when estimating the weights and the thresholds of the five linguistic scales. In other words, the non-fuzzy weights were estimated using the mean of the weights that were produced through Saaty’s eigenvector method. Fuzzy weights were also determined using these sets of weights. The numerical values used to transfer the five linguistic ordered scales (i.e. strongly disagree, disagree, neither disagree nor agree, agree, and strongly agree) were generated from the middle value of the highest likely answered intervals for each scale (see Table 7-7). Fuzzy membership functions representing the subjects’ decision making thresholds were constructed using these answered intervals as well. Since there was no previous study that evaluated service quality using a linguistic scale and then producing numerical service quality using the linguistic responses as outputs, these values, which were generated from the middle of a process of the fuzzy application, were used to produce the results from the conventional methods. The comparison of two values produced by “as similar as possible” methods or a parallel method is more suitable, even though there are small differences between the two values. For this reason, the difference between the output from the fuzzy application and the output from the conventional method was supposed to be small. However, most of the fuzzy outputs were closer to the true values than the output from the conventional
method, even though they were estimated by following a similar procedure and using the same input data.

Unexpectedly, the calculated differences were relatively high in both cases. Some of the responses were not consistent throughout all parts of the experiment. The answers for the overall service quality of signalized intersections is frequently different from the answers for the specific service quality of signalized intersections based on each criterion. For example, the subjects responded with a rating of high overall service quality for an intersection but responded with a low ranking for the questions regarding the specific service quality of the intersection based on each criterion. As a result of these inconsistent responses, a relatively high sum of differences between the observed service quality and the estimated service qualities from both methods was calculated. Figure 7-9 shows the difference between the overall service quality and the specific service quality based on each criterion for intersection 1.

Figure 7-9: Difference between Overall Service Quality and the Specific Service Quality Based on each Criterion of Intersection 1.
In conclusion, a direct validation was conducted using individual perception regarding overall service quality of signalized intersections herein. As mentioned previously, a validation for the study related to transportation user perception is extremely difficult, and there is no previous study conducting it. In this study, the direct validation method dealing with transportation user perception was created and applied to a real transportation problem. Since there was no previous study that evaluated service quality using a linguistic scale and then producing numerical service quality using the linguistic responses as outputs, the conventional method that used to be compared with the fuzzy method also had to be developed herein for the validation. Even though the developed validation method may not be the best method and just one of candidates, the endeavor of the validation, which is conducted in this study, is valuable and can contribute to the study dealing with transportation user perception.

7.4 Indirect Validation of Fuzzy Transportation User Perception

7.4.1 Introduction

In many engineering research projects, it is often a requirement to test numerically if the developed model or results are valid. This numerical validation procedure is also a significantly important step even in a project related to user perception. However, as transportation user perception is subjective and qualitative information and fuzzy approaches are proposed in this study evaluate perception, it is extremely difficult to measure user perception numerically to be able to make a comparison with fuzzy results. None the less, there are many variables that are measurable and have a close relationship with particular transportation user perceptions. Therefore, measuring and using those surrogates may provide some advantages in validating the fuzzy approaches and results.

Based on these considerations, a proposed indirect validation method is illustrated and applied using the evaluated perception of the degree of median safety of Interstate highways and expressways. The proposed method employs a numerical comparison
using a surrogate of a particular transportation user perception. For the numerical comparison, the concept of “Loss Function” was used, and it was applied to evaluate the degree of median safety using the historical CMC crash data as the surrogate measure.

7.4.2 Methodology

An indirect validation of fuzzy results regarding transportation user perception is a validation using a surrogate variable. The surrogate used for the validation process should be measurable and be able to represent a particular transportation user perception evaluated by a fuzzy approach. For example, speed or historical crash data can be used respectively as surrogates of driving conditions or degree of safety perceived by drivers on the roadway. Using these surrogates, a numerical comparison of fuzzy output with observed data provides a means for conducting the validation process. In this study, a numerical comparison of the estimated safety level with the observed crash data is introduced based on the concept of “Loss Function.”

The “loss function” can be defined as the measure of prediction or the measure of the sum of the error. It can show a degree of performance of a model. In other words, it can be used to assess a model based on how closely the developed model predicts the observed events. The model with a lower value of loss function can be considered to be the model producing better performance. In this numerical comparison for the proposed study, two loss functions were used. One function was calculated by the predicted number of events through a developed statistical model. The other function was calculated by a fuzzy output. In general, if the number of events at site $i$ can be predicted ($P_i$), and such events in a time period of interest can be observed ($O_i$), then with $n$ such sites, a loss of the prediction, $Loss(\delta) = \sum_{i=1}^{n} |P_i - O_i|$, can be calculated. Through the comparison of one loss function from a developed statistical model with another loss function from a fuzzy output, the fuzzy output can be validated.

To apply this loss function to the perception of median safety, two loss functions are defined as following equations (Eq. 7.5 and Eq. 7.6):
where

\[ \text{Loss}_s(\delta_s) = \sum_{i=1}^{n} |P_i - O_i| \]  \hspace{1cm} \text{Eq. 7.5} \\
\[ \text{Loss}_f(\delta_f) = \sum_{i=1}^{n} |F_i - O_i| \]  \hspace{1cm} \text{Eq. 7.6} \\

\( \text{Loss}_s(\delta_s) \) = the loss function for the results from a statistic model \\
\( \text{Loss}_f(\delta_f) \) = the loss function for the results from a fuzzy inference system \\
\( F_i \) = the predicted CMC frequency at \( i^{th} \) roadway segment using the fuzzy median safety index (FMSI), which is output from the fuzzy inference system, \( F_i = Y_i \cdot ADT_i \) \\
\( Y_i \) = predicted accident rate for site \( i \) with use of a fuzzy inference system \\
\( O_i \) = the observed CMC frequency \\
\( P_i \) = the predicted CMC frequency using the statistic model \\

The number of CMC crashes at site \( i \) for the time period of interest using FMSI (\( F_i \)) can be calculated by multiplying ADT by the CMC crash rates for site \( i \), which was predicted using the fuzzy inference system.

In the equation for the loss function of fuzzy outputs, the predicted accident rate for site \( i \) developed with the fuzzy inference system was used. However, the final outputs from the fuzzy inference system, the fuzzy median safety indices (FMSI), are not conceptually similar to the predicted accident rate or probability of accidents. When the fuzzy inference system for median safety was developed, the historical CMC crash data were not used as mentioned in chapter 6. The fuzzy inference system was developed using the subjective transportation experts’ opinions and the results of reviewing previous empirical studies of the safety effects of the input variables, rather than using the historical CMC crash data. In other words, the fuzzy inference system was developed based on qualitative information and produced qualitative results as quantitative forms.
The quantitative roadway inventory data and historical crash data, which were used in the statistical prediction model, were used in applying the developed fuzzy inference system and calculating FMSI at roadway segment \( i \). Figure 7-10 explains the development and application of the fuzzy inference system. Therefore, the fuzzy outputs cannot be used directly as the predicted accident rate for site \( i \) in the equation of the loss of the fuzzy inference system.

**Figure 7-10: Statistical Model and Fuzzy Inference System**
The final fuzzy outputs, FMSI, cannot be used as the predicted accident rate or accident probability. For example, “FMSI at roadway site $i = 0.75$” can be interpreted as follows:

1. The degree of safety at roadway $i$ that people generally perceive is 0.75 and the roadway is relatively unsafe because 0.75 FMSI is relatively large.
2. If 100 participants are asked their perceived degree of safety at roadway $i$, about 75 participants will answer that roadway $i$ is not safe.

These two interpretations of FMSI do not explain that the accident rate at roadway $i$ is 0.75. In other words, a 0.75 FMSI does not mean that 75 out of 100 vehicles will have an accident. Therefore, FMSI cannot be used directly to estimate the CMC crash frequency.

For calculating the loss of the fuzzy inference system; however, the predicted accident rate for site $i$ can be “estimated” approximately using the relationship between FMSI and the observed CMC crash rates. In other words, each roadway segment has an individual FMSI value and a CMC crash rate. The mean of the CMC crash rates for the roadway segments that have same value of FMSI can be regarded as the CMC crash rates of those roadway segments. Therefore, the CMC crash rates corresponding to each FMSI value for all roadway segments can be “estimated” and used as the predicted CMC crash rates of site $i$ ($Y_i$) in the study.

For conducting more reliable validation results, the given CMC data set was randomly separated into two sets. Using the one data set, the statistical prediction model was developed, and the CMC crash rates corresponding to each FMSI value were estimated. Using the other data set, two loss functions were calculated using the statistical prediction model and the fuzzy inference system. Table 7-10 shows the details related to how the two data sets were randomly separated.

| Table 7-10: Summary Details of the Two Randomly Separated Data Sets. |
|---------------------------------|-----------------|-----------------|-----------------|-----------------|
|                                | Number of data | Number of CMC crash | Mean of ADT (veh./day) | Mean of Median Width (ft) |
| Data Set 1                     | 6312           | 76               | 6710            | 77              |
| Data Set 2                     | 6469           | 62               | 6635            | 76              |
7.4.3 Application of the Indirect Validation

7.4.3.1 The Loss Using the Statistical Prediction Model

Since CMC is a count variable, a Poisson or negative binomial model is the most appropriated model. It is very important to mention that the development of the statistical model was not the main issue of concern. Given this assertion, the development of the model was conducted by referring to the previous studies that used the same data set, which is the CMC data used in the studies by Donnell et al. (2002) and Donnell (2003), without a thorough investigation of the suitability of these data for this use. These previous studies indicated that the given CMC data exhibited overdispersion, which was indicated by the ratio of the variance over the mean CMC crash frequencies. Due to this discovered overdispersion, the statistical prediction model for the loss function was developed using negative binomial regression. The studies, referred to above, also indicated that the ADT, median width, and pavement width were all statistically significant variables that contributed in explaining the variability in CMC crash frequency and that no interaction effects between all of the predictor variables were found to be statistically significant. Based on these findings, the prediction model was developed using these three variables. The prediction model was as following equation (Eq. 7.7) (Donnell 2003):

\[
N_{\text{CMC}} = e^{-18.8175} \cdot ADT^{1.6441} \cdot e^{-0.0252MW} \cdot e^{0.0458PW}
\]

Eq. 7.7

where

- \( N_{\text{CMC}} \) = number of crossover median collisions per year for one direction of travel
- \( ADT \) = average daily traffic volume for direction of travel evaluated (vehicle/day)
- \( MW \) = median width (ft)
- \( PW \) = pavement width (ft)
Based on this negative binomial model of the previous study, the statistical model for predicting the number of CMC crashes was developed using half of the data set. The LIMDEP software package was used to develop the statistical prediction model. The developed prediction model is as following equation (Eq. 7.8) and Table 7-11:

\[ N_{CMC} = e^{\beta_0} \cdot ADT^{\beta_1} \cdot e^{\beta_2 \cdot MW} \cdot e^{\beta_3 \cdot PW} \]  

**Eq. 7.8**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>T</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-18.8110</td>
<td>2.2747</td>
<td>-8.270</td>
<td>0.0000</td>
</tr>
<tr>
<td>ADT(log)</td>
<td>1.6511</td>
<td>0.2660</td>
<td>6.207</td>
<td>0.0000</td>
</tr>
<tr>
<td>Median Width</td>
<td>-0.0229</td>
<td>0.0074</td>
<td>-3.101</td>
<td>0.0019</td>
</tr>
<tr>
<td>Pavement Width</td>
<td>0.04233</td>
<td>0.0169</td>
<td>2.500</td>
<td>0.0124</td>
</tr>
</tbody>
</table>

Log Likelihood Function = -342.2538

As shown in Table 11, all three variables were statistically significant in explaining the variation in CMC crash frequency.

Using the predicted CMC crash frequency based on the developed statistical model, the “Loss,” for the second data set was calculated. The predicted number of CMC crashes for the second data set was 77.73, and the loss was 121.09.

### 7.4.3.2 The Loss Using the Fuzzy Inference System

The predicted accident rate for site \( i \) was “estimated” using the relationship between FMSI and the observed CMC crash rates. Figure 7-11 and Figure 7-12 show the relationship between FMSI and the observed CMC crash rates. Due to the limitation of the number of data used, bins with 0.05 FMSI intervals were used. The means of the
CMC crash rates for the roadway segments in each bin were regarded as the CMC crash rates of the roadway segment. Through this process, the CMC crash rates corresponding to each FMSI value for all roadway segments were estimated and used as the predicted CMC crash rates of the sites \(Y_i\) in the study. Table 7-12 shows the mean of the CMC frequency and crash rates corresponding to each FMSI.

![Figure 7-11: Mean of Crossover Median Crash Frequency.](image)
Figure 7-12: Mean of Crossover Median Crash Rate.
Using the estimated CMC crash rates corresponding to each FMSI values, the “Loss_i” for the second data set was calculated. The predicted number of CMC crash by FMSI values was 65.80, and the calculated loss was 118.25.

### Table 7-12: Mean of CMC Frequency and Crash Rate Corresponding to the Fuzzy Outputs.

<table>
<thead>
<tr>
<th>Bin</th>
<th>Fuzzy Output (MSI)</th>
<th>Mean of CMC Freq.</th>
<th>CMC Crash rate corresponding FMSI</th>
<th># of data in each bin</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>~ 0.05</td>
<td>0.0000</td>
<td>0.00E+00</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>~ 0.10</td>
<td>0.0053</td>
<td>1.13E-06</td>
<td>4236</td>
</tr>
<tr>
<td>3</td>
<td>~ 0.15</td>
<td>0.0146</td>
<td>1.84E-06</td>
<td>277</td>
</tr>
<tr>
<td>4</td>
<td>~ 0.20</td>
<td>0.0042</td>
<td>4.74E-07</td>
<td>466</td>
</tr>
<tr>
<td>5</td>
<td>~ 0.25</td>
<td>0.0132</td>
<td>1.37E-06</td>
<td>278</td>
</tr>
<tr>
<td>6</td>
<td>~ 0.30</td>
<td>0.0047</td>
<td>4.33E-07</td>
<td>420</td>
</tr>
<tr>
<td>7</td>
<td>~ 0.35</td>
<td>0.0083</td>
<td>1.35E-06</td>
<td>5176</td>
</tr>
<tr>
<td>8</td>
<td>~ 0.40</td>
<td>0.0286</td>
<td>3.50E-06</td>
<td>516</td>
</tr>
<tr>
<td>9</td>
<td>~ 0.45</td>
<td>0.0056</td>
<td>5.98E-07</td>
<td>365</td>
</tr>
<tr>
<td>10</td>
<td>~ 0.50</td>
<td>0.0138</td>
<td>1.27E-06</td>
<td>311</td>
</tr>
<tr>
<td>11</td>
<td>~ 0.55</td>
<td>0.0190</td>
<td>7.61E-07</td>
<td>214</td>
</tr>
<tr>
<td>12</td>
<td>~ 0.60</td>
<td>0.0141</td>
<td>1.03E-06</td>
<td>134</td>
</tr>
<tr>
<td>13</td>
<td>~ 0.65</td>
<td>0.0370</td>
<td>1.91E-06</td>
<td>105</td>
</tr>
<tr>
<td>14</td>
<td>~ 0.70</td>
<td>0.0776</td>
<td>2.98E-06</td>
<td>233</td>
</tr>
<tr>
<td>15</td>
<td>~ 0.75</td>
<td>0.2531</td>
<td>6.97E-06</td>
<td>11</td>
</tr>
<tr>
<td>16</td>
<td>~ 0.80</td>
<td>0.4286</td>
<td>1.45E-05</td>
<td>11</td>
</tr>
<tr>
<td>17</td>
<td>~ 0.85</td>
<td>0.2000</td>
<td>6.96E-06</td>
<td>9</td>
</tr>
<tr>
<td>18</td>
<td>~ 0.90</td>
<td>1.2500</td>
<td>4.23E-05</td>
<td>4</td>
</tr>
<tr>
<td>19</td>
<td>~ 0.95</td>
<td>0.5556</td>
<td>1.55E-05</td>
<td>15</td>
</tr>
<tr>
<td>20</td>
<td>0.95 ~ 1.0</td>
<td>0.0000</td>
<td>0.00E+00</td>
<td>0</td>
</tr>
</tbody>
</table>
7.4.4 Validation Results

Using the results from two loss functions, a comparison of the performance of the statistical model and fuzzy inference system was conducted. As shown Table 7-13, the loss function from the fuzzy inference system was slightly lower than that from the statistical model. Also the total of estimated CMC from the fuzzy inference system was closer to the total of the observed CMC than those from the statistical method. Therefore, it can be concluded that the fuzzy inference system developed using only transportation user perception of median safety, not by historical crash data, is useful as a safety analysis tool and predict approximately the frequencies of cross median crashes. The frequencies of the CMC crashes predicted by the fuzzy inference system are similar with that of the statistical model. Based on this result, it is concluded that what drivers generally perceive regarding the safety aspects of given roadway segments can explain the degree of safety on these roadway segments and this degree of safety corresponds somewhat to historical crash data as well.

<table>
<thead>
<tr>
<th></th>
<th>Total of the observed accident (Data Set 2)</th>
<th>Statistical method</th>
<th>Fuzzy method</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total of the Predicted CMC ($P_i$)</td>
<td>Loss Function</td>
<td>Total of the Estimated CMC ($F_i$)</td>
</tr>
<tr>
<td>Values</td>
<td>62.00</td>
<td>77.73</td>
<td>121.09</td>
</tr>
</tbody>
</table>

7.5 Summary

A validation of studies related to transportation user perception is extremely difficult because there is no existing unique true value of the user’s perception. Because user perception can be different because of individual characteristics and situational
characteristics, it is very challenging to define a unique true value of perception. Based on these considerations, two preliminary validation methods were developed and applied to two different problems related to transportation user perception. The first validation method was a “direct validation,” and it was applied the evaluation of service quality of signalized intersections. The second validation method was an “indirect validation,” and it was applied to the evaluation of median safety on Interstate highways and expressways. The fuzzy aggregation method, one of the two fuzzy approaches used in this dissertation, was used for the application of direct validation, and the fuzzy inference system method, the other approach used herein, was used for the application of the indirect validation.

In the first applications, the fuzzy approaches performed slightly better than conventional approaches, such as a regular weighted average. Also in the second application, the loss function from the fuzzy inference system was slightly lower than that for the statistical model. The total estimated CMCs by the fuzzy inference system was closer to the total observed CMCs than those by the statistical model. Through these results it is concluded that the developed fuzzy approach can analyze what drivers generally perceive from transportation systems when one considers the unique characteristics of humans as transportation users. However, it is important to note that the proposed validation methods, while not ideal, were used as candidate methods for validating transportation user perception. A comparison using a numerical surrogate for perception might not be the most appropriate validation method. Also, it may not produce correct validation results. This is because transportation user perception does not always cause a change in the users’ behavior. For example, though many drivers perceive that the driving conditions along a roadway segment are very good, not all of these drivers increase their speed. Another example might be that while there are roadway segments with no crash history, many drivers perceive a low degree of safety at the segment. Further, as this is a frontier study, the proposed validation methods may be able to be improved, in several important aspects, through future studies.
CHAPTER 8
CONCLUSIONS AND RECOMMENDATIONS

8.1 Research Summary

Users constitute one of the three major components of a transportation system (user, vehicle, and operating environment). One user attribute, user perception, is an important element when considering the concepts of transportation service and transportation safety. However, conventional methods for analyzing transportation user perception have limitations and do not fully explain the user perception phenomena. The perception processes of humans cannot be analyzed and assessed by a binary approach or in a simple quantitative way. The human thought process is subjective and complicated, and human perception usually uses a linguistic approach, as opposed to a numerical approach, to classify, describe, or “value” a system. In addition, transportation user perception is affected by an individual evaluator’s attributes or by situational characteristics.

This research sought to develop a generalized fuzzy approach for analyzing transportation user perception that would consider the unique characteristics of the humans who use transportation systems. Two fuzzy techniques that could be appropriately applied to the study of transportation user perception were selected from various fuzzy approaches. These were fuzzy aggregation and the fuzzy inference system. Then, specific procedures and guidelines for using fuzzy sets to analyze transportation user perception were developed based on these recommended two approaches. The developed fuzzy approaches were applied to two different transportation problems related to user perception. Finally, the proposed fuzzy approaches and their results were compared and preliminarily validated to check for agreement between the approaches. A summary of the work, which details the general fuzzy approaches developed herein can be stated as follows:
Among the many fuzzy techniques, the fuzzy aggregation method and fuzzy inference system were determined to be the most appropriate fuzzy techniques for analysis of transportation user perception. Fuzzy aggregation is a method of aggregating subjective data based on extended algebraic operations using an $\alpha$-cut representation of fuzzy numbers. The proposed fuzzy aggregation used the concept of the fuzzy weighted average wherein fuzzy weights are generated based on the users’ assessments (or perceptions) of the importance of multiple criteria related to a particular transportation system’s attributes. The fuzzy inference system mimics a deductive process that maps given inputs to outputs using fuzzy logic.

There can be many types of fuzzy membership function. These different types of functions were categorized into three classes based on their characteristics and usages. The first class of fuzzy membership function was used to represent how people form their perceptions through certain levels of qualitative variables, such as agreement or satisfaction. The second class was used to represent the relative importance of different criteria, which was used in evaluating individual transportation user perception, such as service quality or degree of highway safety. The last class of fuzzy membership function was used to represent the level of effectiveness (e.g., good, fair, and poor effectiveness of VMS visibility) for different criteria. Using these three classes of fuzzy membership function, the methods of constructing fuzzy membership functions was illustrated. Also, an appropriate construction method for each class of fuzzy membership function was introduced. These included analyst intuition, experimental, and data driven methods. To demonstrate each method, examples were provided.

The fuzzy inference system is the most commonly used. Some problems were identified in its application to transportation user perception. For example, often large numbers of fuzzy rules must be generated to adequately address the problem, and there are no true values of transportation user perception, which are
necessary to generate fuzzy rules. To solve these problems, a hierarchical fuzzy inference system was proposed, and a new fuzzy rule generation method using fuzzy aggregation was developed.

- Perceptions from transportation experts were compared with the perceptions from transportation users to test whether the two perceptions were statistically identical. For this test, experiments using two groups of transportation users were conducted. The results of the experiments indicated that fuzzy membership functions that represented how experts and the general public form their perceptions using certain levels of qualitative variables were not statistically different. However, fuzzy membership functions that represented the relative importance of each criterion were statistically different between the two groups of respondents.

The aforementioned fuzzy approaches were then applied to real transportation problems. Two application case studies were conducted to test the appropriateness of the developed fuzzy methods for analysis of transportation user perception. Another purpose of these application studies was to identify areas where the developed methods might be improved based on learning and experience gained from the application. The first application study was a service quality evaluation by drivers of variable message signs. In this application, the fuzzy aggregation method was used, and overall driver satisfaction was evaluated. The second application study was an evaluation of the degree of median safety based on transportation expert opinion. In this application, the fuzzy inference system using the hierarchical structure and the new fuzzy rule generation method applying the fuzzy aggregation method was employed. The final fuzzy outputs, which represented the perceived degree of median safety, were compared with the observed number of crossover median crashes. Through these two application case studies, the following observations were made. These observations were used to improve the proposed general fuzzy methods for analyzing transportation user perception.
In general, transportation user perception regarding transportation service quality or degree of safety was affected by many factors including roadway geometry, traffic flow, driver characteristics, and other driving conditions.

The magnitude of the effect of each factor on transportation user perception was relatively different between factors and between users. Therefore, a weight of each criterion using the concept of fuzzy sets should be considered for aggregating transportation user perception.

The fuzzy membership functions with a larger number of labels in the fuzzy inference system normally produced a wider spread of defuzzified output. The fuzzy membership functions with a smaller number of labels caused a decrease in the discrimination of the magnitude of input effects on outputs of the fuzzy inference system.

Since the output from a fuzzy inference system represented a transportation user perception, which was a variable having no true value, fuzzy rule generation using conventional methods was not applicable for the fuzzy inference system.

Due to many factors affecting transportation user perception, the fuzzy rule exposure problem (i.e., too many fuzzy rules) was often encountered in the study of transportation user perception.

Based on the findings from the two application studies, the final generalized fuzzy method for analyzing transportation user perception was developed. It was composed of a fuzzy aggregation method using a fuzzy weighted average, a guide for construction of the fuzzy membership function, a method to solve the fuzzy rule exposure problem using a hierarchal fuzzy inference system, and a new fuzzy rule generation method, which was developed based on the experience gained from the application studies.

Despite the difficulty of validating user perception results, a “preliminary” validation of the fuzzy approach and fuzzy results were conducted. Two validation methods were proposed, direct validation and indirect validation. These two validation methods were applied to two different transportation problems related to user perception.
An experimental study evaluating the service quality of signalized intersections was conducted as part of the direct validation. The indirect validation approach used the observed crossover median crashes discussed above. Through both applications, it was found that the fuzzy approaches performed slightly better than conventional analysis approaches, such as regular weighted averages and statistical prediction models.

8.2 Conclusions

Through this study, the following conclusions regarding the study of transportation user perception and the developed fuzzy approach were made:

- In general, transportation user perception was affected by many factors including roadway geometry, traffic flow, driver characteristics, and other driving conditions. Conventional methods for analyzing transportation user perception have limitations and do not fully explain the user perception phenomena.
- The magnitude of the effect of each factor on transportation user perception was relatively different between factors and between users. Analyses considering those differences can produce results that more closely reflect transportation user perception.
- Among the many fuzzy techniques, the fuzzy aggregation method and fuzzy inference system were determined to be the most appropriate fuzzy techniques for analysis of transportation user perception.
- For transportation applications, the categorization of fuzzy membership functions into different “classes” eases the conceptualization and usage of these functions.
- For certain types of transportation-related uses, a hierarchical fuzzy inference system is recommended as a more appropriate type of a fuzzy inference system.
- The new fuzzy rule generation methods used in conjunction with the fuzzy inference system developed herein can be applied in cases where the true output value is unknown, or when the functional relationship between input and output variables is unknown.
The difference between the perception of experts and the general public using certain levels of qualitative variables was not statistically different. However, the relative importance of each criterion that the two groups used to evaluate VMS service quality was statistically different.

Through two preliminary validations, the developed fuzzy approach was clearly indicated as an appropriate method to analyze what drivers generally perceive from transportation systems when considering the unique characteristics of human as transportation users.

The basic concepts and specific procedures of the fuzzy approach developed herein can be used to analyze transportation user perception. More accurate and conceptually realistic analysis of transportation user perception is extremely important for providing better transportation service to the public. By having a better understanding of transportation user perception, transportation systems can be more conducive to providing service with greater user satisfaction. The following are more specific potential contributions of this research:

- Transportation systems can be designed and operated with consideration of what users need, want, and desire.
- Considering individual and situational characteristics when analyzing transportation user perception is possible.
- Overall satisfaction of a transportation system represented by aggregated opinions from groups of transportation users can be evaluated more appropriately, such as results of before-after studies based on user’s satisfaction and evaluations of the improved transportation system or service, including ITS, geometric design, roadway surface condition, traffic information system, roadway delineation, and other transportation systems.
- Transportation safety evaluations based on transportation user perception can be conducted, and in the selection process of roadway segments needing to be improved, the degree of safety perceived by drivers can be used.
- An evaluation of alternatives and selection of the best alternative based on consideration of various decision making processes can be done.
- Other approaches to context-sensitive design with greater consideration of user and community values can be developed.

**8.3 Recommendations for Future Research**

The transportation system exists to provide a high quality of service and safe driving environments for various user groups. Therefore, understanding what a transportation user wants, desires, and needs is important. Transportation engineers and researchers should investigate and consider transportation user perception when designing and operating the transportation system. For example, the information perceived by drivers determines their response or driver behavior. These individual driver behaviors then influence traffic conditions. Therefore, the analysis of transportation user perception can be a paramount consideration in the analysis of traffic flow, evaluation of transportation safety, and evaluation of effects of transportation facilities or service. In many evaluations of transportation systems, users’ opinions have been investigated. However, most of the evaluation studies produce simple statistically aggregated results without considering the variety of user opinion. Through this type of evaluation, subjective data and user opinion cannot be analyzed appropriately using traditional aggregation techniques.

This study is the first effort to analyze transportation user perception while considering the wide range of individual perceptions. Therefore, there are many issues that should be examined as the proposed fuzzy approach is developed further in future research efforts.

- Additional applications to various transportation problems related to user perception should be conducted. Through these applications, developed methods will be extended by addressing current limitations and problems. Fuzzy approaches can be applied to various areas related to transportation user
perception including evaluation of the service quality of various transportation facilities, the decision making process used in dealing with transportation engineering problems, evaluation of ITS services, evaluation of traffic congestion perceived by drivers, analysis of driver comfort perceived from roadway roughness, and other areas related to perception.

- Further investigation regarding experimental design, including the design of survey questions for constructing fuzzy membership functions is needed.

- Even though this study, many methods for constructing fuzzy membership functions were investigated and illustrated, additional research into how to construct more appropriate fuzzy membership function is needed, especially one regarding validation methods of the fuzzy membership functions.

- Fuzzy membership functions in many studies have been constructed for a particular research problem and not for universal application. To increase the applicability of the fuzzy approach, investigation of universal fuzzy membership functions and/or transferable fuzzy membership functions should be conducted.

- Similarly, these same issues should be investigated for fuzzy inference systems. If the fuzzy inference system is developed for only one specific case, then it is not valuable for application to other problems.

- Using additional data, better information regarding the parameters used to determine the shapes (i.e., plotted curves) of fuzzy membership functions, which can produce more precise transportation user perceptions, should be developed.

- Validation of engineering research results is a significantly important process. Validation of human perception results is extremely difficult. In this study, two methods for preliminarily validating the fuzzy approach and its results were provided. However, improvements of validation methods that can produce more accurate validation results are needed.
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APPENDIX A

QUESTIONNAIRES FOR COMPARISON OF USER PERCEPTIONS OF PUBLIC USERS AND EXPERTS
Dear __________

I really appreciate your attention. Your answers will be very helpful for my study. Dr. Pietrucha and I have conducted the study of ‘Developing a Generalized Approach for Analyzing User Perception in Transportation Using Fuzzy Techniques’. We plan to use your opinions as basic information of the how people decide his or her perception of service quality in transportation.

This survey consists of two parts as follows,

1. To investigate how people decide his or her perception with 5 levels of linguistic statements
2. To investigate the degree of importance of each criterion

The results of this survey will be helpful to develop the new method to analyze the human perception related to transportation facilities.

Please be assured that your answers will be used just for this study not for any other purposes and will be kept completely anonymous.

If you have question about this survey or study, please contact me

Thank you very much for your assistance with this study.

Dongmin Lee
Ph.D Candidate
Transportation Engineering, Penn State University
102 Transportation Research Building
e-mail: dul105@psu.edu;
Phone) 814-863-8679
Fax) 814-865-3039
Dear TESC Conference attendee

Thank you for agreeing to participate in this study. Your answers will be very helpful in making improvements to the highway transportation system. The purpose of this survey is to gather information regarding how people perceive transportation service quality.

This survey consists of two parts. The first part investigates how people form their perceptions by having you state your level of agreement or disagreement with some direct statements about transportation system elements. The second part investigates the importance of different criteria used to evaluate some element of transportation service.

The results of this survey will be helpful in developing new methods to analyze user satisfaction with transportation services and facilities.

Rest assured that your answers will be used just for this study and not for any other purposes. Your identity will be kept completely anonymous.

If you have any questions regarding this survey or study, please feel free to contact me. Thank you very much for your assistance with this study.

Dongmin Lee

Ph.D Candidate
Transportation Engineering, Penn State University
102 Transportation Research Building
e-mail: dul105@psu.edu;
Phone) 814-863-8679
Fax) 814-865-3039
PART I

Directions

Assume that you are answering a questionnaire regarding the service quality of traveler information systems, such as the example survey shown below. In the survey, you are asked to assess service quality by considering the different statements and deciding whether you “agree” or “disagree” according to the 5-point scale.

Example survey

How strongly do you agree or disagree with the following statements about variable message signs? (Please use the following response: 1-Strongly Disagree, 2-Disagree, 3-Neither Agree nor Disagree, 4-Agree, or 5-Strongly Agree). Please circle the number

<table>
<thead>
<tr>
<th>Statement</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>a. Variable message signs were clearly visible.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>b. It was easy to read the messages displayed on the variable message signs.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>c. The messages displayed were easy to understand.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>d. The information was accurate.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>e. The information saved you time</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>f. The information let you know what to expect while driving on the turnpike</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>g. The information helped you to avoid congestion.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

If you actually had completed this example survey, how confident would you have been in your responses?
Based on answers you might have given to the questions above, please answer the following questions to classify the five “agreement/disagreement” levels you would have used in answering the survey using a scale from 0% to 100%.

| Example | “I will answer in ‘**Strongly Disagree**’ when my agreement ranges from **0** % to **10** %.” |

| a. | I will answer in ‘**Strongly Disagree**’ when my agreement ranges from _____% to _____%. |
| b. | I will answer in ‘**Disagree**’ when my agreement ranges from _____% to _____%. |
| c. | I will answer in ‘**Neither Agree nor Disagree**’ when my agreement ranges from _____% to _____%. |
| d. | I will answer in ‘**Agree**’ when my agreement ranges from _____% to _____%. |
| e. | I will answer in ‘**Strongly Agree**’ when my agreement ranges from _____% to _____%. |
PART II

This part of the survey investigates the relative importance of different criteria used to evaluate different elements of a transportation service using a “scaling” method. The different criteria, as they relate to variable message signs, are described below.

**Description of criteria**

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Visibility</td>
<td>Whether VMS is clearly visible or not.</td>
</tr>
<tr>
<td>Legibility to read</td>
<td>Whether it is easy to read the messages displayed on the VMS or not.</td>
</tr>
<tr>
<td>Comprehension of message displayed</td>
<td>Whether the messages displayed are easy to understand or not.</td>
</tr>
<tr>
<td>Accuracy of information</td>
<td>Whether the information provided by VMS is accurate or not.</td>
</tr>
<tr>
<td>Usefulness of information</td>
<td>Whether the information provided by VMS helps to save the travel time or not.</td>
</tr>
<tr>
<td>Correspondence between information displayed and expected by drivers</td>
<td>Whether the information provided by VMS let you know what to expect while driving on the road or not.</td>
</tr>
</tbody>
</table>

**Example**

1. *Visibility vs. Legibility to read*

<table>
<thead>
<tr>
<th>Intensity of Importance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scale (1-9)</td>
</tr>
<tr>
<td>1  2  3  4  5  6  7  8  9</td>
</tr>
<tr>
<td>Definition</td>
</tr>
<tr>
<td>Equal  Weak  Strong</td>
</tr>
<tr>
<td>Strong  Very Strong</td>
</tr>
<tr>
<td>Absolute</td>
</tr>
</tbody>
</table>

Please write a number on one line of the pair-wise comparison according to the relative importance of one factor over the other using above scales.

‘Visibility’ over ‘Legibility to read’ with _____ intensity

OR

‘Legibility to read’ over ‘Visibility’ with _______ intensity
1. Visibility vs. Legibility to read

<table>
<thead>
<tr>
<th>Intensity of Importance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scale (1-9)</td>
</tr>
<tr>
<td>1 2 3 4 5 6 7 8 9</td>
</tr>
<tr>
<td>Definition</td>
</tr>
<tr>
<td>Equal</td>
</tr>
<tr>
<td>Weak</td>
</tr>
<tr>
<td>Strong</td>
</tr>
<tr>
<td>Very Strong</td>
</tr>
<tr>
<td>Absolute</td>
</tr>
</tbody>
</table>

Please write a number on one line of the pair-wise comparison according to the relative importance of one factor over the other using above scales.

‘Visibility’ over ‘Legibility to read’ with ________ intensity

OR

‘Legibility to read’ over ‘Visibility’ with ________ intensity

2. Visibility vs. Comprehension of message displayed

<table>
<thead>
<tr>
<th>Intensity of Importance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scale (1-9)</td>
</tr>
<tr>
<td>1 2 3 4 5 6 7 8 9</td>
</tr>
<tr>
<td>Definition</td>
</tr>
<tr>
<td>Equal</td>
</tr>
<tr>
<td>Weak</td>
</tr>
<tr>
<td>Strong</td>
</tr>
<tr>
<td>Very Strong</td>
</tr>
<tr>
<td>Absolute</td>
</tr>
</tbody>
</table>

Please write a number on one line of the pair-wise comparison according to the relative importance of one factor over the other using above scales.

‘Visibility’ over ‘Comprehension of message displayed’ with ________ intensity

OR

‘Comprehension of message displayed’ over ‘Visibility’ with ________ intensity
3. Visibility vs. Accuracy of information

<table>
<thead>
<tr>
<th>Intensity of Importance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scale (1-9)</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Definition</td>
</tr>
<tr>
<td>Equal</td>
</tr>
<tr>
<td>Weak</td>
</tr>
<tr>
<td>Strong</td>
</tr>
<tr>
<td>Very Strong</td>
</tr>
<tr>
<td>Absolute</td>
</tr>
</tbody>
</table>

Please write a number on one line of the pair-wise comparison according to the relative importance of one factor over the other using above scales.

‘Visibility’ over ‘Accuracy of information’ with ________ intensity

OR

‘Accuracy of information’ over ‘Visibility’ with ________ intensity

4. Visibility vs. Usefulness of information

<table>
<thead>
<tr>
<th>Intensity of Importance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scale (1-9)</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Definition</td>
</tr>
<tr>
<td>Equal</td>
</tr>
<tr>
<td>Weak</td>
</tr>
<tr>
<td>Strong</td>
</tr>
<tr>
<td>Very Strong</td>
</tr>
<tr>
<td>Absolute</td>
</tr>
</tbody>
</table>

Please write a number on one line of the pair-wise comparison according to the relative importance of one factor over the other using above scales.

‘Visibility’ over ‘Usefulness of information’ with ________ intensity

OR

‘Usefulness of information’ over ‘Visibility’ with ________ intensity
5. Visibility vs. Correspondence between information displayed and expected by driver

<table>
<thead>
<tr>
<th>Intensity of Importance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scale (1-9)</td>
</tr>
<tr>
<td>1 2 3 4 5 6 7 8 9</td>
</tr>
<tr>
<td>Definition</td>
</tr>
<tr>
<td>Equal</td>
</tr>
<tr>
<td>Weak</td>
</tr>
<tr>
<td>Strong</td>
</tr>
<tr>
<td>Very Strong</td>
</tr>
<tr>
<td>Absolute</td>
</tr>
</tbody>
</table>

Please write a number on one line of the pair-wise comparison according to the relative importance of one factor over the other using above scales.

‘Visibility’ over ‘Correspondence between information displayed and expected by driver’ with ________ intensity

OR

‘Correspondence between information displayed and expected by driver’ over ‘Visibility’ with ________ intensity

6. Legibility to read vs. Comprehension of message displayed

<table>
<thead>
<tr>
<th>Intensity of Importance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scale (1-9)</td>
</tr>
<tr>
<td>1 2 3 4 5 6 7 8 9</td>
</tr>
<tr>
<td>Definition</td>
</tr>
<tr>
<td>Equal</td>
</tr>
<tr>
<td>Weak</td>
</tr>
<tr>
<td>Strong</td>
</tr>
<tr>
<td>Very Strong</td>
</tr>
<tr>
<td>Absolute</td>
</tr>
</tbody>
</table>

Please write a number on one line of the pair-wise comparison according to the relative importance of one factor over the other using above scales.

‘Legibility to read’ over ‘Comprehension of message displayed’ with ________ intensity

OR

‘Comprehension of message displayed’ over ‘Legibility to read’ with ________ intensity
7. Legibility to read vs. Accuracy of information

<table>
<thead>
<tr>
<th>Intensity of Importance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scale (1-9) 1 2 3 4 5 6 7 8 9</td>
</tr>
<tr>
<td>Definition Equal Weak Strong Very Strong Absolute</td>
</tr>
</tbody>
</table>

Please write a number on one line of the pair-wise comparison according to the relative importance of one factor over the other using above scales.

‘Legibility to read’ over ‘Accuracy of information’ with ______ intensity

OR

‘Accuracy of information’ over ‘Legibility to read’ with ______ intensity

8. Legibility to read vs. Usefulness of information

<table>
<thead>
<tr>
<th>Intensity of Importance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scale (1-9) 1 2 3 4 5 6 7 8 9</td>
</tr>
<tr>
<td>Definition Equal Weak Strong Very Strong Absolute</td>
</tr>
</tbody>
</table>

Please write a number on one line of the pair-wise comparison according to the relative importance of one factor over the other using above scales.

‘Legibility to read’ over ‘Usefulness of information’ with ______ intensity

OR

‘Usefulness of information’ over ‘Legibility to read’ with ______ intensity
9. Legibility vs. Correspondence between information displayed and expected by driver

<table>
<thead>
<tr>
<th>Intensity of Importance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scale (1-9)</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Definition</td>
</tr>
<tr>
<td>Equal</td>
</tr>
<tr>
<td>Weak</td>
</tr>
<tr>
<td>Strong</td>
</tr>
<tr>
<td>Very Strong</td>
</tr>
<tr>
<td>Absolute</td>
</tr>
</tbody>
</table>

Please write a number on one line of the pair-wise comparison according to the relative importance of one factor over the other using above scales.

‘Legibility’ over ‘Correspondence between information displayed and expected by driver’ with _______ intensity

OR

‘Correspondence between information displayed and expected by driver’ over ‘Legibility’ with _______ intensity

10. Comprehension of message displayed vs. Accuracy of information

<table>
<thead>
<tr>
<th>Intensity of Importance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scale (1-9)</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Definition</td>
</tr>
<tr>
<td>Equal</td>
</tr>
<tr>
<td>Weak</td>
</tr>
<tr>
<td>Strong</td>
</tr>
<tr>
<td>Very Strong</td>
</tr>
<tr>
<td>Absolute</td>
</tr>
</tbody>
</table>

Please write a number on one line of the pair-wise comparison according to the relative importance of one factor over the other using above scales.

‘Comprehension of message displayed’ over ‘Accuracy of information’ with _______ intensity

OR

‘Accuracy of information’ over ‘Comprehension of message displayed’ with _______ intensity
11. **Comprehension of message displayed vs. Usefulness of information**

**Intensity of Importance**

<table>
<thead>
<tr>
<th>Scale (1-9)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Definition</td>
<td>Equal</td>
<td>Weak</td>
<td>Strong</td>
<td>Very Strong</td>
<td>Absolute</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Please write a number on one line of the pair-wise comparison according to the relative importance of one factor over the other using above scales.

- ‘*Comprehension of message displayed*’ over ‘*Usefulness of information*’ with _______ intensity

  OR

- ‘*Usefulness of information*’ over ‘*Comprehension of message displayed*’ with _______ intensity

12. **Comprehension of message displayed vs. Correspondence between information displayed and expected by driver**

**Intensity of Importance**

<table>
<thead>
<tr>
<th>Scale (1-9)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Definition</td>
<td>Equal</td>
<td>Weak</td>
<td>Strong</td>
<td>Very Strong</td>
<td>Absolute</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Please write a number on one line of the pair-wise comparison according to the relative importance of one factor over the other using above scales.

- ‘*Comprehension of message displayed*’ over ‘*Correspondence between information displayed and expected by driver*’ with _______ intensity

  OR

- ‘*Correspondence between information displayed and expected by driver*’ over ‘*Comprehension of message displayed*’ with _______ intensity
13. Accuracy of information vs. Usefulness of information

<table>
<thead>
<tr>
<th>Intensity of Importance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scale (1-9)</td>
</tr>
<tr>
<td>Definition</td>
</tr>
</tbody>
</table>

Please write a number on one line of the pair-wise comparison according to the relative importance of one factor over the other using above scales.

‘Accuracy of information’ over ‘Usefulness of information’ with ________ intensity

OR

‘Usefulness of information’ over ‘Accuracy of information’ with ________ intensity

14. Accuracy of information vs. Correspondence between information displayed and expected by driver

<table>
<thead>
<tr>
<th>Intensity of Importance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scale (1-9)</td>
</tr>
<tr>
<td>Definition</td>
</tr>
</tbody>
</table>

Please write a number on one line of the pair-wise comparison according to the relative importance of one factor over the other using above scales.

‘Accuracy of information’ over ‘Correspondence between information displayed and expected by driver’ with ________ intensity

OR

‘Correspondence between information displayed and expected by driver’ over ‘Accuracy of information’ with ________ intensity
15. Usefulness of information vs. Correspondence between information displayed and expected by driver

<table>
<thead>
<tr>
<th>Intensity of Importance</th>
<th>Scale (1-9)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Definition</td>
<td></td>
<td>Equal</td>
<td>Weak</td>
<td>Strong</td>
<td>Very Strong</td>
<td>Absolute</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Please write a number on one line of the pair-wise comparison according to the relative importance of one factor over the other using above scales.

‘Usefulness of information’ over ‘Correspondence between information displayed and expected by driver’ with ________ intensity

OR

‘Correspondence between information displayed and expected by driver’ over ‘Usefulness of information’ with ________ intensity
APPENDIX B

MATLAB PROGRAM FOR THE FUZZY AGGREGATION OF VMS SERVICE QUALITY
clear

y = [0 0.5 1 1 0.5 0];
scale_sd = [0 0 0 0.1 0.15 0.2];
scale_d = [0.1 0.15 0.2 0.325 0.4 0.475];
scale_nn = [0.325 0.4 0.475 0.525 0.6 0.675];
scale_a = [0.525 0.6 0.675 0.75 0.85 0.95];
scale_sa = [0.75 0.85 0.95 1 9 9];

%% input and read the data that represent the individual response
load allresponse.txt
% check the data of the individual response
for i=1:322;% This line should be changed to for i=1:322;
    r_v=allresponse(i,1); r_l=allresponse(i,2); r_c=allresponse(i,3); r_a=allresponse(i,4); r_u=allresponse(i,5);
    r_cs=allresponse(i,6);
end

%% Deciding the fuzzy set that represents 5 scale linguistic statement
%% corresponding individual response

%Visibility
if r_v==1;    f_v=scale_sd;
elseif r_v==2;    f_v=scale_d;
elseif r_v==3;    f_v=scale_nn;
elseif r_v==4;    f_v=scale_a;
else r_v==5;    f_v=scale_sa;
end

%Legibility
if r_l==1;    f_l=scale_sd;
elseif r_l==2;    f_l=scale_d;
elseif r_l==3;    f_l=scale_nn;
elseif r_l==4;    f_l=scale_a;
else r_l==5;    f_l=scale_sa;
end

%Comprehension
if r_c==1;    f_c=scale_sd;
elseif r_c==2;    f_c=scale_d;
elseif r_c==3;    f_c=scale_nn;
elseif r_c==4;  f_c=scale_a;
else r_c==5;  f_c=scale_sa;
end

%Accuracy
if r_a==1;  f_a=scale_sd;
elseif r_a==2;  f_a=scale_d;
elseif r_a==3;  f_a=scale_nn;
elseif r_a==4;  f_a=scale_a;
else r_a==5;  f_a=scale_sa;
end

%Usefulness
if r_u==1;  f_u=scale_sd;
elseif r_u==2;  f_u=scale_d;
elseif r_u==3;  f_u=scale_nn;
elseif r_u==4;  f_u=scale_a;
else r_u==5;  f_u=scale_sa;
end

%Correspondence
if r_cs==1;  f_cs=scale_sd;
elseif r_cs==2;  f_cs=scale_d;
elseif r_cs==3;  f_cs=scale_nn;
elseif r_cs==4;  f_cs=scale_a;
else r_cs==5;  f_cs=scale_sa;
end

%save f_criteia.txt f_v f_l f_c f_a f_u f_cs -ascii;

y= [0 0.5 1 0.5 0];
load weight.txt
w_v=weight(1,:); w_l=weight(2,:); w_c=weight(3,:); w_a=weight(4,:); w_u=weight(5,:); w_cs=weight(6,:);
\texttt{p_v}_f= \texttt{max}(p_v,1);
\texttt{p_v}_2=[w_v(1,2)*f_v(1,2), w_v(1,4)*f_v(1,2), w_v(1,5)*f_v(1,2)]; \texttt{\%alpha}=0.5
\texttt{p_v}_2=\texttt{p}_v_2;
\texttt{p_v}_b= \texttt{\texttt{\%alpha}}\texttt{\texttt{=min(p_v,2);}}
\texttt{p_v}_e= \texttt{\texttt{\%alpha}}\texttt{\texttt{=max(p_v,2);}}
\texttt{p_v}_3=[w_v(1,3)*f_v(1,3), w_v(1,3)*f_v(1,4)]; \texttt{\%alpha}=1
\texttt{p_v}_c= \texttt{\texttt{\%alpha}}\texttt{\texttt{=min(p_v,3);}}
\texttt{p_v}_d= \texttt{\texttt{\%alpha}}\texttt{\texttt{=max(p_v,3);}}
\texttt{p_v}=[p_v_a, p_v_b, p_v_c, p_v_d, p_v_e, p_v_f];
\texttt{elseif r_v==1;}
\texttt{p_v}_1=[w_v(1,1)*f_v(1,1), w_v(1,1)*f_v(1,6), w_v(1,5)*f_v(1,1), w_v(1,5)*f_v(1,6)]; \texttt{\%alpha}=0
\texttt{p_v}_1=\texttt{p}_v_1;
\texttt{p_v}_a= w_v(1,1)*f_v(1,6);
\texttt{p_v}_f= w_v(1,5)*f_v(1,6);
\texttt{p_v}_2=[w_v(1,2)*f_v(1,2), w_v(1,2)*f_v(1,5), w_v(1,4)*f_v(1,2), w_v(1,4)*f_v(1,5)]; \texttt{\%alpha}=0.5
\texttt{p_v}_2=\texttt{p}_v_2;
\texttt{p_v}_b= w_v(1,2)*f_v(1,5);
\texttt{p_v}_e= w_v(1,4)*f_v(1,5);
\texttt{p_v}_3=[w_v(1,3)*f_v(1,3), w_v(1,3)*f_v(1,4)]; \texttt{\%alpha}=1
\texttt{p_v}_c= w_v(1,3)*f_v(1,4);
\texttt{p_v}_d= w_v(1,3)*f_v(1,4);
\texttt{p_v}=[p_v_a, p_v_b, p_v_c, p_v_d, p_v_e, p_v_f];
\texttt{else r_v==5;}
\texttt{p_v}_1=[w_v(1,1)*f_v(1,1), w_v(1,1)*f_v(1,6), w_v(1,5)*f_v(1,1), w_v(1,5)*f_v(1,6)]; \texttt{\%alpha}=0
\texttt{p_v}_1=\texttt{p}_v_1;
\texttt{p_v}_a= w_v(1,1)*f_v(1,1);
\texttt{p_v}_f= w_v(1,5)*f_v(1,1);
\texttt{p_v}_2=[w_v(1,2)*f_v(1,2), w_v(1,2)*f_v(1,5), w_v(1,4)*f_v(1,2), w_v(1,4)*f_v(1,5)]; \texttt{\%alpha}=0.5
\texttt{p_v}_2=\texttt{p}_v_2;
\texttt{p_v}_b= w_v(1,2)*f_v(1,2);
\texttt{p_v}_e= w_v(1,4)*f_v(1,2);
\texttt{p_v}_3=[w_v(1,3)*f_v(1,3), w_v(1,3)*f_v(1,4)]; \texttt{\%alpha}=1
\texttt{p_v}_c= w_v(1,3)*f_v(1,3);
\texttt{p_v}_d= w_v(1,3)*f_v(1,4);
\texttt{p_v}=[p_v_a, p_v_b, p_v_c, p_v_d, p_v_e, p_v_f];
end

%Legibility
\texttt{if r_l>1 & r_l<5;}
\texttt{p_l}_1=[w_l(1,1)*f_l(1,1), w_l(1,1)*f_l(1,6), w_l(1,5)*f_l(1,1), w_l(1,5)*f_l(1,6)]; \texttt{\%alpha}=0
\texttt{p\_l\_1=p\_l\_1';}
\texttt{p\_l\_a= min(p\_l\_1);}
\texttt{p\_l\_f= max(p\_l\_1);}
\texttt{p\_l\_2=[w\_l(1,2)*f\_l(1,2), w\_l(1,2)*f\_l(1,5), w\_l(1,4)*f\_l(1,2), w\_l(1,4)*f\_l(1,5)]; %alpha=0.5}
\texttt{p\_l\_2=p\_l\_2';}
\texttt{p\_l\_b= min(p\_l\_2);}
\texttt{p\_l\_e= max(p\_l\_2);}
\texttt{p\_l\_3=[w\_l(1,3)*f\_l(1,3), w\_l(1,3)*f\_l(1,4)]; %alpha=1}
\texttt{p\_l\_c= min(p\_l\_3);}
\texttt{p\_l\_d= max(p\_l\_3);}
\texttt{p\_l=[p\_l\_a, p\_l\_b, p\_l\_c, p\_l\_d, p\_l\_e, p\_l\_f];}
\texttt{elseif \ r\_l==1;}
\texttt{p\_l\_1=[w\_l(1,1)*f\_l(1,1), w\_l(1,1)*f\_l(1,6), w\_l(1,5)*f\_l(1,1), w\_l(1,5)*f\_l(1,6)]; %alpha=0}
\texttt{p\_l\_1=p\_l\_1';}
\texttt{p\_l\_a= w\_l(1,1)*f\_l(1,6);}
\texttt{p\_l\_f= w\_l(1,5)*f\_l(1,6);}
\texttt{p\_l\_2=[w\_l(1,2)*f\_l(1,2), w\_l(1,2)*f\_l(1,5), w\_l(1,4)*f\_l(1,2), w\_l(1,4)*f\_l(1,5)]; %alpha=0.5}
\texttt{p\_l\_2=p\_l\_2';}
\texttt{p\_l\_b= w\_l(1,2)*f\_l(1,5);}
\texttt{p\_l\_e= w\_l(1,4)*f\_l(1,5);}
\texttt{p\_l\_3=[w\_l(1,3)*f\_l(1,3), w\_l(1,3)*f\_l(1,4)]; %alpha=1}
\texttt{p\_l\_c= w\_l(1,3)*f\_l(1,4);}
\texttt{p\_l\_d= w\_l(1,3)*f\_l(1,4);}
\texttt{p\_l=[p\_l\_a, p\_l\_b, p\_l\_c, p\_l\_d, p\_l\_e, p\_l\_f];}
\texttt{else \ r\_l==5;}
\texttt{p\_l\_1=[w\_l(1,1)*f\_l(1,1), w\_l(1,1)*f\_l(1,6), w\_l(1,5)*f\_l(1,1), w\_l(1,5)*f\_l(1,6)]; %alpha=0}
\texttt{p\_l\_1=p\_l\_1';}
\texttt{p\_l\_a= w\_l(1,1)*f\_l(1,1);}
\texttt{p\_l\_f= w\_l(1,5)*f\_l(1,1);}
\texttt{p\_l\_2=[w\_l(1,2)*f\_l(1,2), w\_l(1,2)*f\_l(1,5), w\_l(1,4)*f\_l(1,2), w\_l(1,4)*f\_l(1,5)]; %alpha=0.5}
\texttt{p\_l\_2=p\_l\_2';}
\texttt{p\_l\_b= w\_l(1,2)*f\_l(1,2);}
\texttt{p\_l\_e= w\_l(1,4)*f\_l(1,2);}
\texttt{p\_l\_3=[w\_l(1,3)*f\_l(1,3), w\_l(1,3)*f\_l(1,4)]; %alpha=1}
\texttt{p\_l\_c= w\_l(1,3)*f\_l(1,3);}
\texttt{p\_l\_d= w\_l(1,3)*f\_l(1,4);}
\texttt{p\_l=[p\_l\_a, p\_l\_b, p\_l\_c, p\_l\_d, p\_l\_e, p\_l\_f];}
\texttt{end}

\texttt{\%Comprehension}
if r_c>1 & r_c<5;
  p_c_1=[w_c(1,1)*f_c(1,1), w_c(1,1)*f_c(1,6), w_c(1,5)*f_c(1,1), w_c(1,5)*f_c(1,6)]; %alpha=0
  p_c_1=p_c_1';
  p_c_a= min(p_c_1);
  p_c_f= max(p_c_1);
  p_c_2=[w_c(1,2)*f_c(1,2), w_c(1,2)*f_c(1,5), w_c(1,4)*f_c(1,2), w_c(1,4)*f_c(1,5)]; %alpha=0.5
  p_c_2=p_c_2';
  p_c_b= min(p_c_2);
  p_c_e= max(p_c_2);
  p_c_3=[w_c(1,3)*f_c(1,3), w_c(1,3)*f_c(1,4)]; %alpha=1
  p_c_c= min(p_c_3);
  p_c_d= max(p_c_3);
  p_c=[p_c_a, p_c_b, p_c_c, p_c_d, p_c_e, p_c_f];
else if r_c==1;
  p_c_1=[w_c(1,1)*f_c(1,1), w_c(1,1)*f_c(1,6), w_c(1,5)*f_c(1,1), w_c(1,5)*f_c(1,6)]; %alpha=0
  p_c_1=p_c_1';
  p_c_a= w_c(1,1)*f_c(1,6);
  p_c_f= w_c(1,5)*f_c(1,6);
  p_c_2=[w_c(1,2)*f_c(1,2), w_c(1,2)*f_c(1,5), w_c(1,4)*f_c(1,2), w_c(1,4)*f_c(1,5)]; %alpha=0.5
  p_c_2=p_c_2';
  p_c_b= w_c(1,2)*f_c(1,5);
  p_c_e= w_c(1,4)*f_c(1,5);
  p_c_3=[w_c(1,3)*f_c(1,3), w_c(1,3)*f_c(1,4)]; %alpha=1
  p_c_c= w_c(1,3)*f_c(1,4);
  p_c_d= w_c(1,3)*f_c(1,4);
  p_c=[p_c_a, p_c_b, p_c_c, p_c_d, p_c_e, p_c_f];
else r_c==5;
  p_c_1=[w_c(1,1)*f_c(1,1), w_c(1,1)*f_c(1,6), w_c(1,5)*f_c(1,1), w_c(1,5)*f_c(1,6)]; %alpha=0
  p_c_1=p_c_1';
  p_c_a= w_c(1,1)*f_c(1,1);
  p_c_f= w_c(1,5)*f_c(1,1);
  p_c_2=[w_c(1,2)*f_c(1,2), w_c(1,2)*f_c(1,5), w_c(1,4)*f_c(1,2), w_c(1,4)*f_c(1,5)]; %alpha=0.5
  p_c_2=p_c_2';
  p_c_b= w_c(1,2)*f_c(1,2);
  p_c_e= w_c(1,4)*f_c(1,2);
  p_c_3=[w_c(1,3)*f_c(1,3), w_c(1,3)*f_c(1,4)]; %alpha=1
  p_c_c= w_c(1,3)*f_c(1,3);
  p_c_d= w_c(1,3)*f_c(1,4);
  p_c=[p_c_a, p_c_b, p_c_c, p_c_d, p_c_e, p_c_f];
end
%Accuracy
if r_a>1 & r_a<5;
    p_a_1=[w_a(1,1)*f_a(1,1), w_a(1,1)*f_a(1,6), w_a(1,5)*f_a(1,1), w_a(1,5)*f_a(1,6)]; \text{%alpha}=0
    p_a_1=p_a_1';
    p_a_a= min(p_a_1);
    p_a_f= max(p_a_1);
    p_a_2=[w_a(1,2)*f_a(1,2), w_a(1,2)*f_a(1,5), w_a(1,4)*f_a(1,2), w_a(1,4)*f_a(1,5)]; \text{%alpha}=0.5
    p_a_2=p_a_2';
    p_a_b= min(p_a_2);
    p_a_e= max(p_a_2);
    p_a_3=[w_a(1,3)*f_a(1,3), w_a(1,3)*f_a(1,4)]; \text{%alpha}=1
    p_a_c= min(p_a_3);
    p_a_d= max(p_a_3);
    p_a=[p_a_a, p_a_b, p_a_c, p_a_d, p_a_e, p_a_f];
elseif r_a==1;
    p_a_1=[w_a(1,1)*f_a(1,1), w_a(1,1)*f_a(1,6), w_a(1,5)*f_a(1,1), w_a(1,5)*f_a(1,6)]; \text{%alpha}=0
    p_a_1=p_a_1';
    p_a_a= w_a(1,1)*f_a(1,6);
    p_a_f= w_a(1,5)*f_a(1,6);
    p_a_2=[w_a(1,2)*f_a(1,2), w_a(1,2)*f_a(1,5), w_a(1,4)*f_a(1,2), w_a(1,4)*f_a(1,5)]; \text{%alpha}=0.5
    p_a_2=p_a_2';
    p_a_b= w_a(1,2)*f_a(1,5);
    p_a_e= w_a(1,4)*f_a(1,5);
    p_a_3=[w_a(1,3)*f_a(1,3), w_a(1,3)*f_a(1,4)]; \text{%alpha}=1
    p_a_c= w_a(1,3)*f_a(1,4);
    p_a_d= w_a(1,3)*f_a(1,4);
    p_a=[p_a_a, p_a_b, p_a_c, p_a_d, p_a_e, p_a_f];
else r_a==5;
    p_a_1=[w_a(1,1)*f_a(1,1), w_a(1,1)*f_a(1,6), w_a(1,5)*f_a(1,1), w_a(1,5)*f_a(1,6)]; \text{%alpha}=0
    p_a_1=p_a_1';
    p_a_a= w_a(1,1)*f_a(1,1);
    p_a_f= w_a(1,5)*f_a(1,1);
    p_a_2=[w_a(1,2)*f_a(1,2), w_a(1,2)*f_a(1,5), w_a(1,4)*f_a(1,2), w_a(1,4)*f_a(1,5)]; \text{%alpha}=0.5
    p_a_2=p_a_2';
    p_a_b= w_a(1,2)*f_a(1,2);
    p_a_e= w_a(1,4)*f_a(1,2);
    p_a_3=[w_a(1,3)*f_a(1,3), w_a(1,3)*f_a(1,4)]; \text{%alpha}=1
    p_a_c= w_a(1,3)*f_a(1,3);
    p_a_d= w_a(1,3)*f_a(1,4);
\[ p_a = [p_{a_a}, p_{a_b}, p_{a_c}, p_{a_d}, p_{a_e}, p_{a_f}] \]

end

%Usefulness
if r_u > 1 & r_u < 5;
  \[ p_{u_1} = [w_u(1,1)f_u(1,1), w_u(1,1)f_u(1,6), w_u(1,5)f_u(1,1), w_u(1,5)f_u(1,6)]; \]  \%alpha = 0
  \[ p_{u_1} = p_{u_1}'; \]
  \[ p_{u_a} = \min(p_{u_1}); \]
  \[ p_{u_f} = \max(p_{u_1}); \]
  \[ p_{u_2} = [w_u(1,2)f_u(1,2), w_u(1,2)f_u(1,5), w_u(1,4)f_u(1,2), w_u(1,4)f_u(1,5)]; \]  \%alpha = 0.5
  \[ p_{u_2} = p_{u_2}'; \]
  \[ p_{u_b} = \min(p_{u_2}); \]
  \[ p_{u_e} = \max(p_{u_2}); \]
  \[ p_{u_3} = [w_u(1,3)f_u(1,3), w_u(1,3)f_u(1,4)]; \]  \%alpha = 1
  \[ p_{u_c} = \min(p_{u_3}); \]
  \[ p_{u_d} = \max(p_{u_3}); \]
  \[ p_u = [p_{u_a}, p_{u_b}, p_{u_c}, p_{u_d}, p_{u_e}, p_{u_f}]; \]
elseif r_u == 1;
  \[ p_{u_1} = [w_u(1,1)f_u(1,1), w_u(1,1)f_u(1,6), w_u(1,5)f_u(1,1), w_u(1,5)f_u(1,6)]; \]  \%alpha = 0
  \[ p_{u_1} = p_{u_1}'; \]
  \[ p_{u_a} = w_u(1,1)f_u(1,6); \]
  \[ p_{u_f} = w_u(1,5)f_u(1,6); \]
  \[ p_{u_2} = [w_u(1,2)f_u(1,2), w_u(1,2)f_u(1,5), w_u(1,4)f_u(1,2), w_u(1,4)f_u(1,5)]; \]  \%alpha = 0.5
  \[ p_{u_2} = p_{u_2}'; \]
  \[ p_{u_b} = w_u(1,2)f_u(1,5); \]
  \[ p_{u_e} = w_u(1,4)f_u(1,5); \]
  \[ p_{u_3} = [w_u(1,3)f_u(1,3), w_u(1,3)f_u(1,4)]; \]  \%alpha = 1
  \[ p_{u_c} = w_u(1,3)f_u(1,4); \]
  \[ p_{u_d} = w_u(1,3)f_u(1,4); \]
  \[ p_u = [p_{u_a}, p_{u_b}, p_{u_c}, p_{u_d}, p_{u_e}, p_{u_f}]; \]
else r_u == 5;
  \[ p_{u_1} = [w_u(1,1)f_u(1,1), w_u(1,1)f_u(1,6), w_u(1,5)f_u(1,1), w_u(1,5)f_u(1,6)]; \]  \%alpha = 0
  \[ p_{u_1} = p_{u_1}'; \]
  \[ p_{u_a} = w_u(1,1)f_u(1,1); \]
  \[ p_{u_f} = w_u(1,5)f_u(1,1); \]
  \[ p_{u_2} = [w_u(1,2)f_u(1,2), w_u(1,2)f_u(1,5), w_u(1,4)f_u(1,2), w_u(1,4)f_u(1,5)]; \]  \%alpha = 0.5
  \[ p_{u_2} = p_{u_2}'; \]
  \[ p_{u_b} = w_u(1,2)f_u(1,2); \]
  \[ p_{u_e} = w_u(1,4)f_u(1,2); \]
  \[ p_{u_3} = [w_u(1,3)f_u(1,3), w_u(1,3)f_u(1,4)]; \]  \%alpha = 1
p_u_c = w_u(1,3)*f_u(1,3);
p_u_d = w_u(1,3)*f_u(1,4);
p_u = [p_u_a, p_u_b, p_u_c, p_u_d, p_u_e, p_u_f];
end

% Correspondence
if r_cs > 1 & r_cs < 5;
p_cs_1 = [w_cs(1,1)*f_cs(1,1), w_cs(1,1)*f_cs(1,6), w_cs(1,5)*f_cs(1,1), w_cs(1,5)*f_cs(1,6)]; % alpha=0
p_cs_1 = p_cs_1;
p_cs_a = min(p_cs_1);
p_cs_f = max(p_cs_1);
p_cs_2 = [w_cs(1,2)*f_cs(1,2), w_cs(1,2)*f_cs(1,5), w_cs(1,4)*f_cs(1,2), w_cs(1,4)*f_cs(1,5)];
% alpha=0.5
p_cs_2 = p_cs_2;
p_cs_b = min(p_cs_2);
p_cs_e = max(p_cs_2);
p_cs_3 = [w_cs(1,3)*f_cs(1,3), w_cs(1,3)*f_cs(1,4)]; % alpha=1
p_cs_c = min(p_cs_3);
p_cs_d = max(p_cs_3);
p_cs = [p_cs_a, p_cs_b, p_cs_c, p_cs_d, p_cs_e, p_cs_f];
elseif r_cs == 1;
p_cs_1 = [w_cs(1,1)*f_cs(1,1), w_cs(1,1)*f_cs(1,6), w_cs(1,5)*f_cs(1,1), w_cs(1,5)*f_cs(1,6)]; % alpha=0
p_cs_1 = p_cs_1;
p_cs_a = w_cs(1,1)*f_cs(1,6);
p_cs_f = w_cs(1,5)*f_cs(1,6);
p_cs_2 = [w_cs(1,2)*f_cs(1,2), w_cs(1,2)*f_cs(1,5), w_cs(1,4)*f_cs(1,2), w_cs(1,4)*f_cs(1,5)];
% alpha=0.5
p_cs_2 = p_cs_2;
p_cs_b = w_cs(1,2)*f_cs(1,5);
p_cs_e = w_cs(1,4)*f_cs(1,5);
p_cs_3 = [w_cs(1,3)*f_cs(1,3), w_cs(1,3)*f_cs(1,4)]; % alpha=1
p_cs_c = w_cs(1,3)*f_cs(1,4);
p_cs_d = w_cs(1,3)*f_cs(1,4);
p_cs = [p_cs_a, p_cs_b, p_cs_c, p_cs_d, p_cs_e, p_cs_f];
else r_cs == 5;
p_cs_1 = [w_cs(1,1)*f_cs(1,1), w_cs(1,1)*f_cs(1,6), w_cs(1,5)*f_cs(1,1), w_cs(1,5)*f_cs(1,6)]; % alpha=0
p_cs_1 = p_cs_1;
p_cs_a = w_cs(1,1)*f_cs(1,1);
p_cs_f = w_cs(1,5)*f_cs(1,1);
\[ p_{\text{cs}_2} = [w_{\text{cs}(1,2)} f_{\text{cs}(1,2)}, w_{\text{cs}(1,2)} f_{\text{cs}(1,5)}, w_{\text{cs}(1,4)} f_{\text{cs}(1,2)}, w_{\text{cs}(1,4)} f_{\text{cs}(1,5)}]; \]

%%% alpha = 0.5

\[ p_{\text{cs}_2} = p_{\text{cs}_2}'; \]

\[ p_{\text{cs}_b} = w_{\text{cs}(1,2)} f_{\text{cs}(1,2)}; \]

\[ p_{\text{cs}_e} = w_{\text{cs}(1,4)} f_{\text{cs}(1,2)}; \]

\[ p_{\text{cs}_3} = [w_{\text{cs}(1,3)} f_{\text{cs}(1,3)}, w_{\text{cs}(1,3)} f_{\text{cs}(1,4)}]; \]

%%% alpha = 1

\[ p_{\text{cs}_c} = w_{\text{cs}(1,3)} f_{\text{cs}(1,3)}; \]

\[ p_{\text{cs}_d} = w_{\text{cs}(1,3)} f_{\text{cs}(1,4)}; \]

\[ p_{\text{cs}} = [p_{\text{cs}_a}, p_{\text{cs}_b}, p_{\text{cs}_c}, p_{\text{cs}_d}, p_{\text{cs}_e}, p_{\text{cs}_f}]; \]

end

%%% Average of perception of 6 criteria

\[ p = [p_v_a + p_l_a + p_c_a + p_a_a + p_u_a + p_{\text{cs}_a}, p_v_b + p_l_b + p_c_b + p_a_b + p_u_b + p_{\text{cs}_b}, p_v_c + p_l_c + p_c_c + p_u_c + p_{\text{cs}_c}, p_v_d + p_l_d + p_c_d + p_a_d + p_u_d + p_{\text{cs}_d}, p_v_e + p_l_e + p_c_e + p_u_e + p_{\text{cs}_e}, p_v_f + p_l_f + p_c_f + p_a_f + p_u_f + p_{\text{cs}_f}]; \]

end; % ending for loops
APPENDIX C

MATLAB PROGRAM FOR THE FUZZY INFERENCE SYSTEM OF MEDIAN SAFETY
clear

y = [0 0.5 1 1 0.5 0];

%% Fuzzy membership function for Median Width
%% High numerical values indicate more dangerous condition
%% less numerical values indicate less dangerous and safer condition

%% f_MW1 = "Good" for median width
%% f_MW2 = "Fair" for median width
%% f_MW3 = "Poor" for median width

%% f_HC1 = "No curve" for Horizontal Curve
%% f_HC2 = "Curved" for Horizontal Curve

%% f_OP1 = "Low" for Operating Speed
%% f_OP2 = "Medium" for Operating Speed
%% f_OP3 = "High" for Operating Speed

%% f_MCS1 = "Acceptable" for Median Cross Slope
%% f_MCS2 = "Poor" for Median Cross Slope

%% f_SW1 = "Good" for Shoulder Width
%% f_SW2 = "Fair" for Shoulder Width
%% f_SW3 = "Poor" for Shoulder Width

load fmf_geometric_2.txt

%% fmf_geometric is a 13 by 6 metrix

f_MW1 = fmf_geometric_2(1,:);
%% f_MW2 = fmf_geometric_2(2,:);
%% f_MW3 = fmf_geometric_2(3,:);

f_HC1 = fmf_geometric_2(4,:);
%% f_HC2 = fmf_geometric_2(5,:);
%% f_HC3 = fmf_geometric_2(6,:);

f_OP2 = fmf_geometric_2(7,:);
%% f_OP3 = fmf_geometric_2(8,:);

f_MCS1 = fmf_geometric_2(9,:);
%% f_MCS2 = fmf_geometric_2(10,:);
%% f_MCS3 = fmf_geometric_2(11,:);

f_SW1 = fmf_geometric_2(11,:);
%% f_SW2 = fmf_geometric_2(12,:);
%% f_SW3 = fmf_geometric_2(13,:);
input and read the data that represent the individual response load cases.txt

% check the data of the individual response
for i=1:108;% This line should be changed to for i=1:120;
c_MW=cases(i,1); c_HC=cases(i,2); c_OP=cases(i,3); c_MCS=cases(i,4); c_SW=cases(i,5);

% Deciding the fuzzy set that represents each factor corresponding 108 cases

%Median Width
if c_MW==1;  f_MW=f_MW1;
elseif c_MW==2;  f_MW=f_MW2;
else c_MW==3;  f_MW=f_MW3;
end

%Horizontal Curve
if c_HC==1;  f_HC=f_HC1;
else c_HC==2;  f_HC=f_HC2;
end

%Operating Speed
if c_OP==1;  f_OP=f_OP1;
elseif c_OP==2;  f_OP=f_OP2;
else c_OP==3;  f_OP=f_OP3;
end

%Median Cross Slope
if c_MCS==1;  f_MCS=f_MCS1;
else c_MCS==2;  f_MCS=f_MCS2;
end

%Soulder Width
if c_SW==1;    f_SW=f_SW1;
elseif c_SW==2;    f_SW=f_SW2;
else c_SW==3;    f_SW=f_SW3;
end

y= [0 0.5 1 0.5 0];
load weight.txt
w_MW=weight(1,:); w_HC=weight(2,:); w_OP=weight(3,:); w_MCS=weight(4,:); w_SW=weight(5,:);

%Geometric condition for j case

%Median Width

p_MW_1=[w_MW(1,1)*f_MW(1,1), w_MW(1,1)*f_MW(1,6), w_MW(1,5)*f_MW(1,1),
        w_MW(1,5)*f_MW(1,6)]; %alpha=0
p_MW_1=p_MW_1';
p_MW_a= min(p_MW_1);
p_MW_f= max(p_MW_1);
p_MW_2=[w_MW(1,2)*f_MW(1,2), w_MW(1,2)*f_MW(1,5), w_MW(1,4)*f_MW(1,2),
        w_MW(1,4)*f_MW(1,5)]; %alpha=0.5
p_MW_2=p_MW_2';
p_MW_b= min(p_MW_2);
p_MW_e= max(p_MW_2);
p_MW_3=[w_MW(1,3)*f_MW(1,3), w_MW(1,3)*f_MW(1,4)]; %alpha=1
p_MW_c= min(p_MW_3);
p_MW_d= max(p_MW_3);
p_MW=[p_MW_a, p_MW_b, p_MW_c, p_MW_d, p_MW_e, p_MW_f];

%Horizontal Curve

p_HC_1=[w_HC(1,1)*f_HC(1,1), w_HC(1,1)*f_HC(1,6), w_HC(1,5)*f_HC(1,1), w_HC(1,5)*f_HC(1,6)]; %alpha=0
p_HC_1=p_HC_1';
p_HC_a= min(p_HC_1);
p_HC_f= max(p_HC_1);
p_HC_2=[w_HC(1,2)*f_HC(1,2), w_HC(1,2)*f_HC(1,5), w_HC(1,4)*f_HC(1,2), w_HC(1,4)*f_HC(1,5)]; %alpha=0.5
p_HC_2=p_HC_2';
p_HC_b= min(p_HC_2);
p_HC_e= max(p_HC_2);
p_HC_3=[w_HC(1,3)*f_HC(1,3), w_HC(1,3)*f_HC(1,4)]; %alpha=1
\[ p_{HC. c} = \min(p_{HC. 3}) \]
\[ p_{HC. d} = \max(p_{HC. 3}) \]
\[ p_{HC} = [p_{HC. a}, p_{HC. b}, p_{HC. c}, p_{HC. d}, p_{HC. e}, p_{HC. f}] \]

%Operating Speed
\[ p_{OP. 1} = [w_{OP}(1,1) \cdot f_{OP}(1,1), w_{OP}(1,1) \cdot f_{OP}(1,6), w_{OP}(1,5) \cdot f_{OP}(1,1), w_{OP}(1,5) \cdot f_{OP}(1,6)] \]
%\( \alpha = 0 \)
\[ p_{OP. 1} = p_{OP. 1}' \]
\[ p_{OP. a} = \min(p_{OP. 1}) \]
\[ p_{OP. f} = \max(p_{OP. 1}) \]
\[ p_{OP. 2} = [w_{OP}(1,2) \cdot f_{OP}(1,2), w_{OP}(1,2) \cdot f_{OP}(1,5), w_{OP}(1,4) \cdot f_{OP}(1,2), w_{OP}(1,4) \cdot f_{OP}(1,5)] \]
%\( \alpha = 0.5 \)
\[ p_{OP. 2} = p_{OP. 2}' \]
\[ p_{OP. b} = \min(p_{OP. 2}) \]
\[ p_{OP. e} = \max(p_{OP. 2}) \]
\[ p_{OP. 3} = [w_{OP}(1,3) \cdot f_{OP}(1,3), w_{OP}(1,3) \cdot f_{OP}(1,4)] \]
%\( \alpha = 1 \)
\[ p_{OP. c} = \min(p_{OP. 3}) \]
\[ p_{OP. d} = \max(p_{OP. 3}) \]
\[ p_{OP} = [p_{OP. a}, p_{OP. b}, p_{OP. c}, p_{OP. d}, p_{OP. e}, p_{OP. f}] \]

%Median Cross Slope
\[ p_{MCS. 1} = [w_{MCS}(1,1) \cdot f_{MCS}(1,1), w_{MCS}(1,1) \cdot f_{MCS}(1,6), w_{MCS}(1,5) \cdot f_{MCS}(1,1), w_{MCS}(1,5) \cdot f_{MCS}(1,6)] \]
%\( \alpha = 0 \)
\[ p_{MCS. 1} = p_{MCS. 1}' \]
\[ p_{MCS. a} = \min(p_{MCS. 1}) \]
\[ p_{MCS. f} = \max(p_{MCS. 1}) \]
\[ p_{MCS. 2} = [w_{MCS}(1,2) \cdot f_{MCS}(1,2), w_{MCS}(1,2) \cdot f_{MCS}(1,5), w_{MCS}(1,4) \cdot f_{MCS}(1,2), w_{MCS}(1,4) \cdot f_{MCS}(1,5)] \]
%\( \alpha = 0.5 \)
\[ p_{MCS. 2} = p_{MCS. 2}' \]
\[ p_{MCS. b} = \min(p_{MCS. 2}) \]
\[ p_{MCS. e} = \max(p_{MCS. 2}) \]
\[ p_{MCS. 3} = [w_{MCS}(1,3) \cdot f_{MCS}(1,3), w_{MCS}(1,3) \cdot f_{MCS}(1,4)] \]
%\( \alpha = 1 \)
\[ p_{MCS. c} = \min(p_{MCS. 3}) \]
\[ p_{MCS. d} = \max(p_{MCS. 3}) \]
\[ p_{MCS} = [p_{MCS. a}, p_{MCS. b}, p_{MCS. c}, p_{MCS. d}, p_{MCS. e}, p_{MCS. f}] \]

%Shoulder Width
\[ p_{SW. 1} = [w_{SW}(1,1) \cdot f_{SW}(1,1), w_{SW}(1,1) \cdot f_{SW}(1,6), w_{SW}(1,5) \cdot f_{SW}(1,1), w_{SW}(1,5) \cdot f_{SW}(1,6)] \]
%\( \alpha = 0 \)
\[ p_{SW. 1} = p_{SW. 1}' \]
\[ p_{SW\_a} = \min(p_{SW\_1}) \]
\[ p_{SW\_f} = \max(p_{SW\_1}) \]
\[ p_{SW\_2} = [w_{SW}(1,2)f_{SW}(1,2), w_{SW}(1,2)f_{SW}(1,5), w_{SW}(1,4)f_{SW}(1,2), w_{SW}(1,4)f_{SW}(1,5)] \]
\[ \%\alpha = 0.5 \]
\[ p_{SW\_2} = p_{SW\_2}'; \]
\[ p_{SW\_b} = \min(p_{SW\_2}) \]
\[ p_{SW\_e} = \max(p_{SW\_2}) \]
\[ p_{SW\_3} = [w_{SW}(1,3)f_{SW}(1,3), w_{SW}(1,3)f_{SW}(1,4)] \]
\[ \%\alpha = 1 \]
\[ p_{SW\_c} = \min(p_{SW\_3}) \]
\[ p_{SW\_d} = \max(p_{SW\_3}) \]
\[ p_{SW} = [p_{SW\_a}, p_{SW\_b}, p_{SW\_c}, p_{SW\_d}, p_{SW\_e}, p_{SW\_f}] \]

% aggregate geometric condition
\[ p = [p_{MW\_a} + p_{HC\_a} + p_{OP\_a} + p_{MCS\_a} + p_{SW\_a}, p_{MW\_b} + p_{HC\_b} + p_{OP\_b} + p_{MCS\_b} + p_{SW\_b}, p_{MW\_c} + p_{HC\_c} + p_{OP\_c} + p_{MCS\_c} + p_{SW\_c}, p_{MW\_d} + p_{HC\_d} + p_{OP\_d} + p_{MCS\_d} + p_{SW\_d}, p_{MW\_e} + p_{HC\_e} + p_{OP\_e} + p_{MCS\_e} + p_{SW\_e}, p_{MW\_f} + p_{HC\_f} + p_{OP\_f} + p_{MCS\_f} + p_{SW\_f}] \]

\[ g\_condition(i,:) = p; \]

end; % ending for loops

\[ g\_condition \]

\[
\text{save } g\_condition\_2.txt \text{ } g\_condition \text{ } \text{-ascii}
\]

2. Lower Level Fuzzy Inference System

Clear;

load g\_data.txt

% check the data of the individual response
for i=1:12781; % This line should be changed by the number of data;
MW=g\_data(i,1); HC=g\_data(i,2); OP=g\_data(i,3); MCS=g\_data(i,4); SW=g\_data(i,5);

a = readfis('Geometric4\_1');
gci(i,:) = evalfis([MW HC OP MCS SW], a);
i

gci(i,:)
end; % ending for loops_
%gci
save gci_result_4_1.txt gci -ascii;
3. Upper Level Fuzzy Inference System

clear;

load final_data5_2.txt
% check the data of the individual response
for i=1:12781;% This line should be changed by the number of data;
ADT=final_data5_2(i,1); FGI=final_data5_2(i,2);

    a = readfis('Final_logic21');
    msi(i,:)=evalfis([ADT FGI], a);
    i
    msi(i,:)

end; % ending for loops
%msi
save msi_result21_2.txt msi -ascii;
APPENDIX D

QUESTIONNAIRES FOR THE EXPERIMENT FOR DIRECT VALIDATION
PART I

Directions

Now, we will watch 12 roadway scenes, and each scene shows a different intersection. After watching each scene, please answer the following question regarding your perception of the overall service quality of this signalized intersection. Each scene has about 10 seconds as a pause. Please answer the following question during the time.

Example

Q1. What is your perception of the service quality at this intersection? (Please circle one of the linguistic values given below.)

   Poor   Acceptable   Good

Q2. What percentage of satisfaction do you get from this signalized intersection? (Please write your perception of this intersection’s service quality with numerical values ranging from 0 to 100. “0” means least satisfactory, and “100” means most satisfactory.)

45

Questions on the next page is example questions for intersection #1 (Scene 1) and #3 (Scene 3) out of total 12 intersections.
SCENE 1

Q1. What is your perception of the service quality at this intersection? (Please circle one of the linguistic values given below.)

Poor          Acceptable          Good

Q2. What percentage of satisfaction do you get from this signalized intersection? (Please write your perception of this intersection’s service quality with numerical values ranging from 0 to 100. “0” means least satisfactory, and “100” means most satisfactory.)

SCENE 3

Q1. What is your perception of the service quality at this intersection? (Please circle one of the linguistic values given below.)

Poor          Acceptable          Good

Q2. What percentage of satisfaction do you get from this signalized intersection? (Please write your perception of this intersection’s service quality with numerical values ranging from 0 to 100. “0” means least satisfactory, and “100” means most satisfactory.)
PART II

Directions
This part of the survey investigates the relative importance of different criteria used to evaluate different elements of a transportation service using a “scaling” method. The different criteria, as they relate to service quality of signalized intersection, are described below.

Description of criteria

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Length of waiting time</td>
<td>Whether the waiting time due to the signal is tolerable or not.</td>
</tr>
<tr>
<td>Length of gaps in traffic on the cross street</td>
<td>Whether the length of gaps in traffic on the cross street while drivers wait for a green indication on their road is tolerable or not.</td>
</tr>
<tr>
<td>Traffic signal operation</td>
<td>Whether the traffic signals operate efficiently or not.</td>
</tr>
<tr>
<td>Traffic signal visibility</td>
<td>Whether the traffic signals are clearly visible or not.</td>
</tr>
<tr>
<td>Intersection guidance information</td>
<td>Whether the intersection guidance information functions well or not. (traffic signs, road markings, or other delineation devices)</td>
</tr>
<tr>
<td>Physical features of the intersection</td>
<td>Whether the physical features of the intersection are good or not. (turning exclusive lane, intersection angle, corner clearance, sight distance)</td>
</tr>
</tbody>
</table>

Example

2. *Length of waiting time vs. Length of gaps in traffic on the cross street*

a. Please mark the one that you think is more important

   - Length of waiting time __
   - Length of gaps in traffic on the cross street _√_

b. Then please circle a value on the below scale indicating the intensity of importance (How much one is more important than other one)

   **Intensity of Importance**

<table>
<thead>
<tr>
<th>Scale (1-9)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
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<tbody>
<tr>
<td>Definition</td>
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<td>Strong</td>
<td>Very Strong</td>
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</table>

※ This example answer means that ‘Length of gaps in traffic on the cross street’ is strongly more important than ‘Length of waiting time.’
Questions

1. **Length of waiting time vs. Length of gaps in traffic on the cross street**

   a. Please mark one that you think is more important

   

   Length of waiting time ______
   Length of gaps in traffic on the cross street ______

   b. Then please circle below scale regarding intensity of importance (How much one is more important than other one)

   ![Intensity of Importance Table]

2. **Length of waiting time vs. Traffic signal operation**

   a. Please mark one that you think is more important

   

   Length of waiting time ______
   Traffic signal operation ______

   b. Then please circle below scale regarding intensity of importance (How much one is more important than other one)

   ![Intensity of Importance Table]
3. Length of waiting time vs. Traffic signal visibility

a. Please mark one that you think is more important

   Length of waiting time ____
   Traffic signal visibility ____

b. Then please circle below scale regarding intensity of importance (How much one is more important than other one)

   Intensity of Importance

<table>
<thead>
<tr>
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</table>

4. Length of waiting time vs. Intersection guidance information

a. Please mark one that you think is more important

   Length of waiting time ____
   Intersection guidance information ____

b. Then please circle below scale regarding intensity of importance (How much one is more important than other one)

   Intensity of Importance

<table>
<thead>
<tr>
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</tbody>
</table>
5. **Length of waiting time vs. Physical features of the intersection**

a. Please mark one that you think is more important

   **Length of waiting time ____**  
   **Physical features of the intersection ____**

b. Then please circle below scale regarding intensity of importance (How much one is more important than other one)

   **Intensity of Importance**

<table>
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</tbody>
</table>

6. **Length of gaps in traffic on the cross street vs. Traffic signal operation**

a. Please mark one that you think is more important

   **Length of gaps in traffic on the cross street ____**  
   **Traffic signal operation ____**

b. Then please circle below scale regarding intensity of importance (How much one is more important than other one)

   **Intensity of Importance**

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<tr>
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</tbody>
</table>
7. **Length of gaps in traffic on the cross street vs. Traffic signal visibility**

a. Please mark one that you think is more important

   *Length of gaps in traffic on the cross street*** ___
   *Traffic signal visibility*** ___

b. Then please circle below scale regarding intensity of importance (How much one is more important than other one)

   **Intensity of Importance**

<table>
<thead>
<tr>
<th>Scale (1-9)</th>
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</tbody>
</table>

8. **Length of gaps in traffic on the cross street vs. Intersection guidance information**

a. Please mark one that you think is more important

   *Length of gaps in traffic on the cross street*** ___
   *Intersection guidance information*** ___

b. Then please circle below scale regarding intensity of importance (How much one is more important than other one)

   **Intensity of Importance**

<table>
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</tr>
</tbody>
</table>
9. **Length of gaps in traffic on the cross street vs. Physical features of the intersection**

   a. Please mark one that you think is more important

   *Length of gaps in traffic on the cross street***___
   *Physical features of the intersection***___

   b. Then please circle below scale regarding intensity of importance (How much one is more important than other one)

   **Intensity of Importance**

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<tr>
<th>Scale (1-9)</th>
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</tr>
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</table>

10. **Traffic signal operation vs. Traffic signal visibility**

    a. Please mark one that you think is more important

    *Traffic signal operation***___
    *Traffic signal visibility***___

    b. Then please circle below scale regarding intensity of importance (How much one is more important than other one)

    **Intensity of Importance**

    | Scale (1-9) | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
    |------------|---|---|---|---|---|---|---|---|---|
    | Definition | Equal | Weak | Strong | Very Strong | Absolute |
11. **Traffic signal operation vs. Intersection guidance information**

   a. Please mark one that you think is more important

   *Traffic signal operation _____
   *Intersection guidance information _____

   b. Then please circle below scale regarding intensity of importance (How much one is more important than other one)

<table>
<thead>
<tr>
<th>Intensity of Importance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scale (1-9)</td>
</tr>
<tr>
<td>1 2 3 4 5 6 7 8 9</td>
</tr>
<tr>
<td>Definition</td>
</tr>
<tr>
<td>Equal  Weak  Strong  Very Strong  Absolute</td>
</tr>
</tbody>
</table>

12. **Traffic signal operation vs. Physical features of the intersection**

    a. Please mark one that you think is more important

    *Traffic signal operation _____
    *Physical features of the intersection _____

    b. Then please circle below scale regarding intensity of importance (How much one is more important than other one)

    | Intensity of Importance |
    |--------------------------|
    | Scale (1-9)              |
    | 1 2 3 4 5 6 7 8 9       |
    | Definition               |
    | Equal  Weak  Strong  Very Strong  Absolute |
13. Traffic signal visibility vs. Intersection guidance information

a. Please mark one that you think is more important

Traffic signal visibility _____
Intersection guidance information _____

b. Then please circle below scale regarding intensity of importance (How much one is more important than other one)

Intensity of Importance

<table>
<thead>
<tr>
<th>Scale (1-9)</th>
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</tbody>
</table>

14. Traffic signal visibility vs. Physical features of the intersection

a. Please mark one that you think is more important

Traffic signal visibility _____
Physical features of the intersection _____

b. Then please circle below scale regarding intensity of importance (How much one is more important than other one)

Intensity of Importance

<table>
<thead>
<tr>
<th>Scale (1-9)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Definition</td>
<td>Equal</td>
<td>Weak</td>
<td>Strong</td>
<td>Very Strong</td>
<td>Absolute</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
15. **Intersection guidance information vs. Physical features of the intersection**

a. Please mark one that you think is more important

    *Intersection guidance information ___*
    *Physical features of the intersection ___*

b. Then please circle below scale regarding intensity of importance (How much one is more important than other one)

<table>
<thead>
<tr>
<th>Scale (1-9)</th>
<th>1</th>
<th>2</th>
<th>3</th>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
PART III

Directions

Assume that you are answering a questionnaire regarding the service quality of a signalized intersection, such as the example survey shown below. In the survey, you are asked to assess service quality by considering the different statements and deciding whether you “agree” or “disagree” according to the 5-point scale.

Example

※ You are not supposed to answer this example survey

<table>
<thead>
<tr>
<th>How strongly do you agree or disagree with the following statements about a signalized intersection? (Please use the following response: 1-Strongly Disagree, 2-Disagree, 3-Neither Agree nor Disagree, 4-Agree, or 5-Strongly Agree). Please circle the number that indicates your response.</th>
</tr>
</thead>
<tbody>
<tr>
<td>a. The waiting time (delay) due to the signal is not too long.</td>
</tr>
<tr>
<td>b. The length of the gaps in traffic on the cross street while waiting for a green signal is not too long.</td>
</tr>
<tr>
<td>c. The order and the length of the signal indications are satisfactory.</td>
</tr>
<tr>
<td>d. The traffic signal is visible.</td>
</tr>
<tr>
<td>e. The quality of the guidance information at the intersection is satisfactory (such as traffic signs, road markings, or other delineation device).</td>
</tr>
<tr>
<td>f. The physical features of the intersection are satisfactory (such as exclusive turning lanes, ability to see other approaches, curb radius, sight distance).</td>
</tr>
</tbody>
</table>
Questions

Based on answers you might have given to the questions above, please answer the following questions to classify the five “agreement/disagreement” levels you would have used in answering the survey using a scale from 0% to 100%.

- Five Linguistic scales for “agreement/disagreement
  - Strongly Disagree
  - Disagree
  - Neither Agree nor Disagree
  - Agree
  - Strongly Agree

Example
“"I will answer in ‘Strongly Disagree’ when my agreement ranges from _0_ % to _10_ %.”

Please answer the following questions

a. I will answer in ‘Strongly Disagree’ when my agreement ranges from _____% to ____%. 

b. I will answer in ‘Disagree’ when my agreement ranges from _____% to ____%. 

c. I will answer in ‘Neither Agree nor Disagree’ when my agreement ranges from _____% to ____%. 

d. I will answer in ‘Agree’ when my agreement ranges from _____% to ____%. 

e. I will answer in ‘Strongly Agree’ when my agreement ranges from _____% to _____%. 

Part IV

Directions
This part of the survey investigates your perception regarding service quality of the signalized intersection on the screen based on criteria according to a 5-point scale. You will watch 12 scenes of the signalized intersections. Each scene will be showing twice to have enough time to answer 6 questions based on 6 criteria.

Example

| How strongly do you agree or disagree with the following statements about the signalized intersection on the screen? (Please use the following response: 1-Strongly Disagree, 2-Disagree, 3-Neither Agree nor Disagree, 4-Agree, or 5-Strongly Agree). Please circle the number |
|---|---|---|---|---|
| a. The waiting time (delay) due to signal is not too long and satisfactory. | 1 | 2 | 3 | 4 | 5 |
| b. The length of gaps in traffic on the cross street while drivers wait for a green phase on a road is not too long and satisfactory. | 1 | 2 | 3 | 4 | 5 |
| c. The efficient operation of traffic signals is satisfactory. | 1 | 2 | 3 | 4 | 5 |
| d. The visibility of traffic signals is satisfactory. | 1 | 2 | 3 | 4 | 5 |
| e. The quality of the guide system of the intersection is satisfactory (such as traffic sign, road marking and other delineation device). | 1 | 2 | 3 | 4 | 5 |
| f. The features of the intersection are satisfactory. (such as turning exclusive lane, intersection angle, corner clearance, sight distance) | 1 | 2 | 3 | 4 | 5 |

Questions

Questions on the next page is an example question for intersection #1 (scene 1) out of total 12 intersections (scenes)
**SCENE 1**

How strongly do you agree or disagree with the following statements about the signalized intersection on the screen? (Please use the following response: 1-Strongly Disagree, 2-Disagree, 3-Neither Agree nor Disagree, 4-Agree, or 5-Strongly Agree). Please circle the number

<table>
<thead>
<tr>
<th>Statement</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>a. The waiting time (delay) due to signal is not too long and satisfactory.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>b. The length of gaps in traffic on the cross street while drivers wait for a green phase on a road is not too long and satisfactory.</td>
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<td></td>
<td></td>
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<td></td>
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<tr>
<td>c. The efficient operation of traffic signals is satisfactory.</td>
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<td>f. The features of the intersection are satisfactory. (such as turning exclusive lane, intersection angle, corner clearance, sight distance)</td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>
VITA

Dongmin Lee

EDUCATION

May 2006  The Pennsylvania State University, University Park, PA
Doctor of Philosophy, Civil Engineering
(Major: Transportation Eng., Minor: Statistics)

February 2000  University of Seoul, SEOUL, KOREA
Master of Science, Urban Engineering (Major: Transportation Eng.)

February 1995  University of Seoul, SEOUL, KOREA
Bachelor of Science, Urban Engineering (Major: Transportation Eng.)

RESEARCH EXPERIENCE

January 2002 – May 2006  Graduate Research Assistant, Pennsylvania Transportation Institute
The Pennsylvania State University, University Park, PA

Researched transportation issues associated with highway geometric design and highway safety and involved following three projects;
- Pavement Marking Retroreflectivity (FHWA Project)
- Geometric Design for Work Zones on High-Speed Facilities (NCHRP Project 3-69),
- Evaluation of Highway Safety Treatments on Operational Characteristics (PennDOT Project)

November 2000 – June 2001  Researcher, Department of Urban Transportation,
Seoul Development Institute, SEOUL, KOREA

Involved in the project of Evaluation of the ATIS of the 1st Namsan tunnel and Installation of the basic plan for the ATIS of the 3rd Namsan tunnel and Seoul Overpass

April 1999 – Oct 2000  Transportation Engineer, Yangkwang Inc., SEOUL, KOREA

SELECTED JOURNAL PUBLICATIONS/PRESENTATION

