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COMPARISON OF CLASSICAL ANALYTIC HIERARCHY PROCESS (AHP) APPROACH AND FUZZY AHP APPROACH IN MULTIPLE-CRITERIA DECISION MAKING FOR COMMERCIAL VEHICLE INFORMATION SYSTEMS AND NETWORKS (CVISN) PROJECT

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APPROACH AND FUZZY AHP APPROACH IN MULTIPLE-CRITERIA

DECISION MAKING FOR COMMERCIAL VEHICLE INFORMATION

SYSTEMS AND NETWORKS (CVISN) PROJECT

By

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COMPARISON OF CLASSICAL ANALYTIC HIERARCHY PROCESS (AHP)

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Liyuan Zhang, M.S.

University of Nebraska, 2010

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Radio Frequency Identification (RFID) has emerged as an important technology with many possible applications in a wide variety of fields. It is said that RFID can perform well in transportation system. Nebraska Department of Motor Vehicles (NEDMV) is using this technique to perform an analysis on utilizing RFID license plates to assist with Commercial Vehicle Information Systems and Networks (CVISN) program with the cooperation of many other stakeholders. Previous House of Quality (HOQ) analysis evaluates stakeholders' needs and provides the pairwise comparison values of six important technical requirements for each stakeholder. Based on these, this research aims to seek for the comprehensive ranking of the six technical requirements.

The weights of different technical requirements vary a lot according to different stakeholders. As a result, assumptions are made to make it possible that fuzzy analytic hierarchy process (AHP) approach could be used to give weight rankings of this multiple-criteria decision making problem. Problem comes out naturally that whether or not fuzzy AHP is appropriate to solve this problem. To verify the feasibility of

application of fuzzy AHP to CVISN project problem, benchmarking comparison of classical AHP and fuzzy AHP approaches is performed. The comparison bases on a series of statistical models with 240 randomly generated statistical data. Results of comparison indicate that the pairwise weight values of AHP approach positively affect the difference between the two approaches, and fuzzy AHP could narrow the differences of weights among different criteria.

Benchmarking models provide basic parameters, based on which prediction intervals are built to verify the outcomes of CVISN project given by fuzzy AHP. Results show that fuzzy AHP is an appropriate approach for CVISN project. Finally a comprehensive weight vector of six technical requirements is provided by fuzzy AHP, catering to the requirements of further research on choosing a best RFID system.

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CHAPTER 1. INTRODUCTION

Radio Frequency Identification (RFID) was commercially introduced in the early

1980's and it has become a mature technology as a replacement for other technologies

such as barcodes (Stone et al.). Its application has been intended to many fields.

A RFID system contains four components: RFID tags, RFID antennas, RFID

readers, and middleware. RFID tags have the ability to read, write, transmit, store and

upload information. With such advantages compared to bar codes, RFID technology

offers an inexpensive and non-labor intensive way to track and identify objectives in

real time without contact or line-of-sight.

The transportation system, which requires a high level of accurate and reliable

tracking information, is a preeminent field which allows RFID technology to

showcase its advantages. RFID is a useful technology to improve the transportation

efficiency, safety and visibility. In order to utilize automated technologies for more

effective roadside enforcement, pertinent information must be accessible and

collected in a reliable way. Therefore studies on the factors that influence data gaining

are important to the implementation of RFID technology in the transportation system.

Nebraska has currently attained Commercial Vehicle Information Systems and

Networks (CVISN) Core Compliance, with the aim of offseting the costs of

conducting a feasibility study on RFID embedded license plates in transportation

systems that may ultimately be expanded for national use. Previous studies on this

project showed that six significant technical factors affected the performance of

embedding RFID into license plates most. These factors are: the RFID tag

(transponder) and reader distance, physical limitation, read rate, display of relevant information, RFID tag number, and manufacturing cost. This research studies further on the importance of these six factors to find out which one is the most important to the embedding of RFID systems into license plates. Results of this research provide theoretical foundation to future study on selecting the best RFID system on the basis of the factors, which can be seen as multiple criteria.

The factors given by previous studies were in the form of house of quality (HOQ). However, they were weighted differently among stakeholders, making the criteria ranking confusing. In order to avoid misleading solutions, a fuzzy Analytic Hierarchy Process (AHP) was used, which considered more possible pairwise comparisons presented by different stakeholders.

AHP is an approach for decision making under complex criteria at different levels. It gives the ranking of multiple criteria by multiple decision makers based on pairwise comparison of these criteria. Thus, it is a robust way to mathematically transform decision makers' judgments and references into numerical results. Unfortunately, some of the decision data cannot be assessed exactly in reality, or different decision makers may express their opinions differently by means of preference relations [1]. To avoid these uncertainties, fuzzy AHP is developed and applied under those fuzzy circumstances, with respect to possible pairwise comparison values among different stakeholders.

Instead of restricted comparison value, Fuzzy AHP allows decision makers to present their references within a reasonable interval if they are not sure about them.

These intervals result in fuzzy judgment matrix, corresponding to the constant value judgment matrix of classical AHP. The significance of difference stakeholders are equal to each other. Thus, the comparison values given by difference stakeholders for a certain pair of factors are considered as the interval of the comparison value for such pair of factors given by a virtual single decision maker. In this way, fuzzy AHP can be applied to rank the factors based on HOQ for CVISN project.

This research is divided into three parts. First, this research compares fuzzy AHP approach with classical AHP approach based on a series of randomly generated data. Results include what factors that affect the difference between these two approaches most and in what way they affect the difference. In addition, statistical models about the relationship between the factors and the difference are also built to present the visually numerical influence. Second, this research ranks the six factors given by previous HOQ studies by both AHP and fuzzy AHP approaches for CVISN project. Likewise, statistical data about independent and predicted variables according to the models in the first part, which need to be verified, were calculated. Third, this research estimates the predicted intervals for each predicted variable based on the models. Then the intervals were used to verify the results given by part two. Finally, conclusions about whether fuzzy AHP was appropriate for CVISN project and the rank of six factors were provided.

CHAPTER 2. BACKGROUND

2.1.   History of AHP and Fuzzy AHP

2.1.1.   Multiple-Criteria Decision Making (MCDM) and AHP

Decision situations involve a multitude of objectives or decision criteria which

may be incommensurate and conflict with one another [2]. Decision analysis

considers the paradigm in which an individual decision maker (or decision group)

contemplates a choice of action in an uncertain environment. Decision analysis is

designed to help the individual make a choice among a set of pre-specified

alternatives. The decision making process relies on information about the alternatives.

The quality of information in any decision situation can vary from the

scientifically-derived hard data to subjective interpretations; from certainty about

decision outcomes (deterministic information) to uncertain outcomes represented by

probabilities and fuzzy numbers. This diversity in type and quality of information

about a decision problem calls for methods and techniques that can assist in

information processing. Ultimately, these methods and techniques such as

Multiple-Criteria Decision Making (MCDM) may lead to better decisions [3].

MCDM is often supported by a set of techniques to help decision makers who

are faced with such decision situations of making numerous and sometimes

conflicting evaluations. MCDM aims at identifying these conflicts, comparing and

evaluating these alternatives according to the diverse criteria, deriving a way to come

to a best compromise solution in a transparent process [4].

Unlike methods that assume the availability of measurements, measurements in

MCDM are derived or interpreted subjectively as indicators of the strength of various

preferences. Preferences differ from decision maker to decision maker, so the outcome depends on who is making the decision and what their goals and preferences are [5]. Since MCDM involves a certain element of subjectiveness, the morals and ethics of the persons implementing MCDM play a significant part in the accuracy and fairness of MCDM's conclusions. The ethical point is very important when one is making a decision that seriously impacts on other people, as opposed to a personal decision.

There are many MCDM methods in use today, the main one of which is Analytic Hierarchy Process (AHP). AHP method, which was pioneered by Satty in 1971, is developed to meet the great challenges of decision situations that are brought by multiple or even conflicting criteria [6]. Rather than prescribing a "correct" decision, the AHP helps the decision makers find the one that best suits their needs and their understanding of the problem.

AHP approach is most useful where teams of people are working on complex problems, especially those with high stakes, involving human perceptions and judgments, whose resolutions have long-term repercussions [7]. It has unique advantages when important elements of the decision are difficult to quantify or compare, or where communication among team members is impeded by their different specializations, terminologies, or perspectives. It is a widely used decision making analysis aid that models unstructured problems in political, economic, social, and management sciences [8]. It aims to rank decision alternatives and select the best one for a complex multi-criteria decision-making problem [9] by using pairwise

comparison of those criteria.

Decision situations to which the AHP can be applied include the following six aspects [10].

(1)   Choice - The selection of one alternative from a given set of alternatives, usually where there are multiple decision criteria involved.

(2)   Ranking - Putting a set of alternatives in order from most to least desirable.

(3)   Prioritization - Determining the relative merit of members of a set of alternatives, as opposed to selecting a single one or merely ranking them.

(4)   Resource allocation - Apportioning resources among a set of alternatives.

(5)   Benchmarking - Comparing the processes in one's own organization with those of other best-of-breed organizations.

(6)   Quality management - Dealing with the multidimensional aspects of quality and quality improvement.

The AHP provides a comprehensive and rational framework for structuring a decision problem, for representing and quantifying its elements, for relating those elements to overall goals, and for evaluating alternative solutions. The essence of AHP process is to create a hierarchy tree based on the decomposition of a complex problem, with the goal at the top, criteria and/or sub-criteria at levels, and decision alternatives at the bottom, as shown in Figure 2.1. Elements are then compared in pairs to assess their relative preference and decisions are made according to the comparison and calculation.
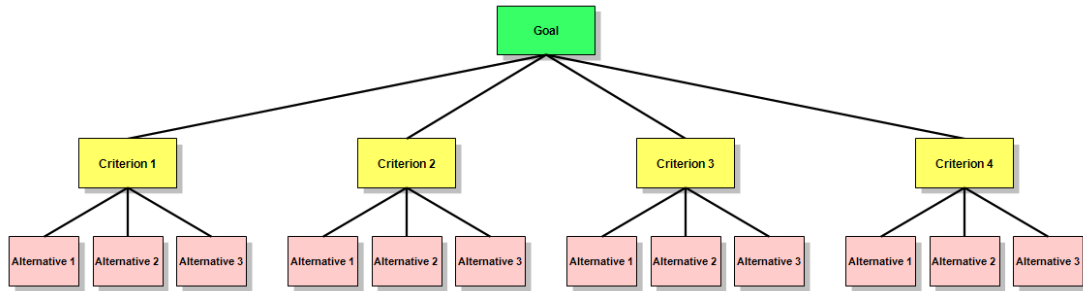
Figure 2.1.   Structure of AHP process

The basic principle of AHP includes the following procedures [11, 12, 13, and 14]:

(1)   Define the unstructured problem and state clearly the goal of the problem;

(2)   Identify the factors that influence the overall goal;

(3)   Decompose the complex overall evaluation goal into hierarchical structure with detailed decision criteria and variables, which are manageable;

(4)   Select a scale method, employ pairwise comparisons among decision criteria and form comparison matrices;

(5)   Estimate the relative priorities of the decision criteria by using method like eigenvalue or the geometric mean;

(6)   Check the consistency property of matrices to ensure the judging consistence; aggregate the relative priorities of decision criteria;

(7)   Aggregate the final weight coefficient vector which represents the relative importance of each alternative with respect to the goal stated at the top of the hierarchy.

Among all, the pairwise comparison matrix is particularly important because it is the key to transform subjective priorities to computable values according to decision makers' preferences.

These pairwise comparisons are usually gained by experts via questionnaire and other approach like Delphi methodology. They are made by using a preference scale to assign numerical values to different levels of preference [15]. Usually, scale used for AHP is from 1 to 9 to reflect the importance of one factor over another. The fundamental scale for pairwise comparisons is shown in Table 2.1.

Table 2.1. Fundamental scale for pairwise comparisons

Intensity of Importance	Definition	Explanation
1	Equal importance	Two elements contribute equally to the objective
3	Moderate importance	Experience and judgment slightly favor one element over another
5	Strong importance	Experience and judgment strongly favor one element over another
7	Very strong importance	One element is favored very strongly over another; its dominance is demonstrated in practice
9	Extreme importance	The evidence favoring one element over another is of the highest possible order of affirmation
Intensities of 2, 4, 6, and 8 can be used to express intermediate values. Intensities 1.1, 1.2, 1.3, etc can be used for elements that are very close in importance.		

The reciprocals, such as 1/3, 1/5, 1/7, 1/9, etc., indicate the opposite respectively of the values 3, 5, 7, 9, etc. [16].

Selection of numerical scale provided by the experts is important in the validity of the decision making tool. It aims to quantify the priorities of the linguistic pairwise comparisons and it can be presented by means of different numerical scales and the geometrical scale is the most commonly used ones [17, 18]. Technically, the priorities

must capture the dominance of the order expressed in the judgments of pairwise comparisons, and for classic AHP method they should be unique [19].

2.1.2. Fuzzy Set Theory (FST) and Fuzzy AHP

Nevertheless, there is an extensive literature which addresses the situation in the real world where the comparison ratios are imprecise judgments. In many practical cases, the human preference is uncertain or decision makers might be reluctant or unable to assign exact numerical values to the comparison judgments or individual judgments in group decision making might be variant. Since some of the evaluation criteria are subjective and qualitative in nature, it is very difficult for the decision maker to express the preferences using exact numerical values and to provide exact pairwise comparison judgments. It is more desirable for the decision maker to use interval or fuzzy evaluations [20]. Essentially, the uncertainty in the preference judgments gives rise to uncertainty in the ranking of alternatives as well as difficulty in determining consistency of preferences [21]. The classical deterministic AHP method tends to be less effective in conveying the imprecision and vagueness characteristics. This led to the development of Fuzzy Set Theory (FST) by Zadeh (1965), who proposed that the key elements in human thinking are not numbers but labels of fuzzy sets.

FST is a powerful tool to handle imprecise data and fuzzy expressions that are more natural for humans than rigid mathematical rules and equations [19]. It has been used to model systems that are hard to define precisely. As a methodology, it incorporates imprecision and subjectivity into the model formulation and solution

process. FST is now applied to problems in extensive fields, involving engineering, business, medical and related health sciences, and the natural sciences [22].

FST permits the gradual assessment of the membership of elements in a set; this is described with the aid of a membership function valued in the real unit interval [0, 1]. Fuzzy sets generalize classical sets, since the indicator functions of classical sets are special cases of the membership functions of fuzzy sets, if the latter only take values 0 or 1 [23].

FST defines set membership as a possibility distribution. On the basis of the possibility distribution of FST, fuzzy AHP technique is developed as an advanced analytical method developed from the traditional AHP. Despite the convenience of AHP in handling both quantitative and qualitative criteria of multiple criteria decision making problems based on decision makers' judgments, fuzzy AHP can reduce or even eliminate the fuzziness and vagueness existing in many decision making problems may contribute to the imprecise judgments of decision makers in conventional AHP approaches [24].

There are researches compare fuzzy AHP and classical AHP. These research studies are divided mainly into two aspects. The first are the methods to make fuzzy comparison matrices. Early studies on fuzzy AHP approach were classified in that aspect. Researchers worked on the theoretical methods and what the differences were between the two approaches. Once the factors that affected the differences were understood, methods based on the factors were made to improve the fuzzy AHP. The second aspect was the practical application of both approaches. Later studies were

mainly categorized in this second aspect. Research was focused simply on the difference between the results given by these two approaches, in the form of two weight vectors given by corresponding approaches. The connection between these two aspects is a gap in previous studies. This paper combined them together to explore how the factors that give rise to the differences affect the weight vector given by Fuzzy AHP and the differences.

The earliest method work in fuzzy AHP appeared in a paper by van Laarhoven and Pedrycz, who suggested a fuzzy logarithmic least squares method (LLSM) to obtain triangular fuzzy weights from a triangular fuzzy comparison matrix. Then Lootsma's logarithmic least square was used to derive local fuzzy priorities. Later, Buckley utilized the geometric mean method to calculate fuzzy weights. Recently in 1996, Chang used the extent analysis method and the principle of Triangular Fuzzy Numbers (TFN) comparison to obtain the priorities of alternatives from pairwise comparisons [25, and 26]. Among all, Chang's extent analysis method is the most popular one because the steps of this approach are simpler and also it has been successfully applied in many fields [21].

Chang's extent analysis on fuzzy AHP depends on the degree of possibilities of each criterion. On the basis of different possible weight values gained by different decision makers, for a particular level on the hierarchy the pairwise comparison matrix is constructed and the corresponding TFN for the criterion are placed, which contains three levels of comparison values. These values are following the scale showed in Table 2.2. Then definite steps are conducted to find the overall triangular

fuzzy values for each criterion. After the weights are obtained, they are normalized and called the final importance weights. At last, according to the criterion weights, the weights for each alternative are calculated and a final decision made.

Table 2.2. Triangular Fuzzy Number (TFN) value

statement	TFN
absolute	(7/2,4,9/2)
very strong	(5/2,3,7/2)
fairly strong	(3/2,2,5/2)
weak	(2/3,1,3/2)
equal	(1,1,1)

While comparing Chang's fuzzy AHP and classical AHP, Ozdagoglu [27] says that the result of the fuzzy intersection can be obtained as zero which means that the corresponding criterion has no importance. What is more, it concludes that if the information evaluations are certain, classical method should be preferred; if the information evaluations are not certain, fuzzy method should be preferred. Meixner [28] also shows that by use of Chang's method, putting an emphasis on the most important criteria could be an advantage. Also, there is a slight shift from less important to more important criteria. In addition, the use of the geometric mean instead of a minimum and maximum operation seems to be of advantage when aggregating fuzzy numbers. Otherwise the calculated weights tend to exceed a tolerable range because of isolated runaway values. On the contrary, paper by Wang etc. [25] argues about the disadvantages of Chang's method by giving three adverse numerical examples. These examples show that the weights determined by the extent analysis method do not represent the relative importance or the method could not make full use of all the fuzzy comparison matrices information.

Once the factors that influence the difference between classical AHP and fuzzy AHP and the numerical weight results gained by these two approaches are defined, the problem is how the factors affect the difference. The relationship between these two parts is a gap in knowledge. If the effects of the factors were know, the application of fuzzy AHP will be used more properly in situations that are more suitable to utilize fuzzy AHP other than classical AHP.

2.2. Literature review of Ratio Frequency Identification (RFID)

2.2.1. History of RFID

RFID technologies originated from radar theories that were discovered by the allied forces during World War II and have been commercially available since the early 1980's. Over the last three decades, RFID has been used for a wide variety of applications such as transportation freight tracking, retail theft prevention, library systems, automotive manufacturing, postal services, animal tracking, and so on [29] to improve the efficiency of object tracking and management.

The demonstration of the first continuous wave radio generation and transmission of radio signals by Ernst F.W. Alexanderson in 1906 indicated the beginning of modern radio communication. Later in the early 20th century, technologies of radar appeared. They were used to detect and locate objects by sending out radio waves and receiving the reflection of them. Then the position and speed of the objective could be determined by the radio wave reflection. Since RFID is based on the combination of radio broadcast technology and radar, it is not

unexpected that the convergence of these two radio disciplines and the thoughts of RFID occurred on the heels of the development of radar [30].

In 1945 Léon Theremin invented an espionage tool for the Soviet Union. This device converted listening by retransmitting incident radio waves with audio information. The principle that supported this device was that sound waves vibrated a diaphragm which slightly altered the shape of the resonator and the resonator modulated the reflected radio frequency. This device, even though it was not an identification tag, was considered to be a predecessor of RFID technology, because it was likewise passive, being energized and activated by electromagnetic waves from an outside source [31].

Another early work exploring RFID is the landmark paper by Harry Stockman, "Communication by Means of Reflected Power," published in 1948, where the author stated that "Evidently, considerable research and development work has to be done before the remaining basic problems in reflected-power communication are solved, and before the field of useful applications is explored."

The 1960s were the prelude to the RFID explosion of the 1970s. In the 1970s developers, inventors, companies, academic institutions, and government laboratories were actively working on RFID, and notable advances were being realized at research laboratories and academic institutions [32].

In 1973, Mario Cardullo received the patent for his device, which was typically the first true ancestor of modern RFID. This is because the device was a passive radio transponder with memory that can be read and wrote [33]. At the same year, another

patent was awarded to Charles Walton who used a passive transponder to unlock a door without a key. Walton embedded a transponder storing a valid identity number into a card so as to communicate a signal to a reader near the door. Then the door would be unlocked when the reader detected this number. Also at the year of 1973, Steven Depp, Alfred Koelle, and Robert Freyman showed reflected power RFID tags for both passive and semi-passive at the Los Alamos National Laboratory.

The first patent to be associated with the abbreviation RFID was granted to Charles Walton in 1983 [34]. The decade of the 1980s, RFID technology had been fully implemented and entered the mainstream as a commercially application. Untill the 1990s, the standards of RFID emerged, which allowed this technology extent to international wide deployment.

Nowadays, RFID explosion is continuing. The application is trying to break new paths to different fields, calling for new advanced techniques to back up. A typical way for future application is the micro of RFID, which requests special raw material and manufacturing technique. Reasonable assumptions state that this micro RFID has a brilliant application foreground in the field of medicine.

2.2.2. Component of RFID

RIFD is basically a technology to identify or track objects such as a product, animal, or person automatically using communication via electromagnetic waves without human intervention. A RFID system allows wireless data communication between a stationary location and a movable object or between movable objects from a distance [30, 35].

A RFID system comprises three components, tags, readers, antennas, and middleware software, as shown in Figure 2.2. The components are introduced here one by one.
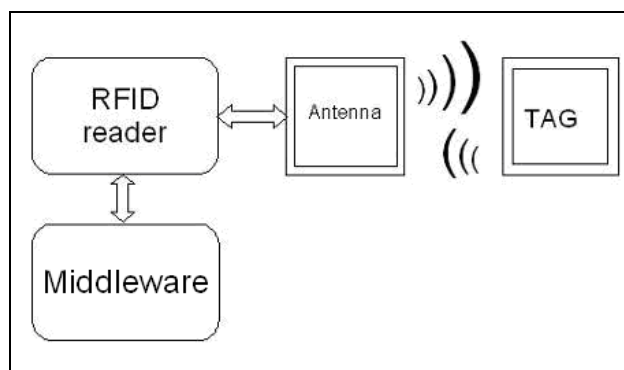
Figure 2.2.   Structure of a RFID system

2.2.2.1. RFID tags

RFID tags are the heart of an RFID system due to their duty of storing the basic information of the tracked object, which consist of identity, location, date, price, state, speed, etc. Tags often consist of a microchip with an internally attached coiled antenna. This digital memory chip stores the information of a unique object. RFID tags could be in different shapes for different purpose.

Some tags include batteries, expandable memory, and sensors [36]. According to the capability, tags are divided into the following types [37].

2.2.2.1.1.   Passive tags

Passive tags have no battery and the communication range of them is limited to approximately 3 meters or less. Once the passive tag enters the response range of a reader, RF signal powers the tag and the chip inside modulates the waves and transmits the information, which was captured by the reader who then sends back to

the terminal system. Figure 2.3 shows two samples of passive tags.
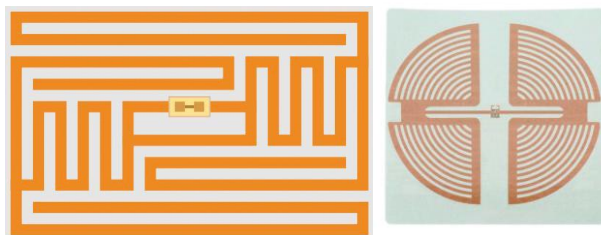
Figure 2.3.   Passive RFID tags

2.2.2.1.2.   Active tag

Active tags have a battery inside and are usually strong enough to be read in a far distance around 100 meters or more. Other than passive tags, active tags can directly broadcasts RF signals wirelessly on their own when they enter the response range of a reader. Figure 2.4 shows two samples of active tags, coming from RF Code and Savi companies respectively.

Figure 2.4.   Active RFID tags

2.2.2.1.3.   Read-only tags

Read-only tags contain data that are pre-written onto them by the tag manufacturer or distributor. The lack of capability of being rewritten with any additional information all through the whole supply chain makes them the least expensive RFID tags.

2.2.2.1.4.   Write-once tags

Write-once tags could be added with information by the user for just one time.

2.2.2.1.5.   Full read-write tags

Full read-write tags enable the users to rewrite data whenever needed.

2.2.2.2.   RFID antennas

A RFID antenna is a conductive element that permits data exchanging between tags and readers. Coiled antenna is used for passive tags. By using the energy provided by the reader's carrier signal, coiled antenna emits electromagnetic range to activate the passive tags which enter in this response range. Then it receives information which is broadcasted by the tags' antenna and transmits them back to readers. Sometimes RFID antennas are attached to RFID readers as an integrative component.

2.2.2.3. RFID readers

RFID readers have the function of converting radio waves from RFID tags into a form that can be passed to middleware. They interrogate tags' information by broadcasting a specific RF signal. Then the tags will respond to this signal by transmitting back a unique serial number or Electronic Product Code (EPC). Finally RFID readers receive the information and convert and send them to middleware uses as CPU data [38].

There are two types of RFID readers according to the capacity of removability.

2.2.2.3.1.   Mobile readers

Mobile readers are usually in the form of two common devices. One is handheld reader which is the same as handheld barcode scanner; and the other one is readers attached to a mobile device such as a forklift embedding RFID reader. Mobile readers

have the advantage of portability. Figure 2.5 shows a handheld RFID reader and

Figure 2.6 shows a forklift RFID reader.

Figure 2.5.   Handheld RFID reader

Figure 2.6.   Forklift RFID reader

2.2.2.3.2.   Fix readers

Fix readers are stationary and mounted to strategic fixed position such as the

portal RFID readers. Readers capture information when objects with RFID tags pass

by or near the position. Fixed readers have advantage of larger reading range [39].

Generally, fixed readers have their antenna attached to them. Figure 2.7 is a fixed

reader and antenna of Savi Company.

Figure 2.7.   Fix reader and antenna of Savi Company

2.2.2.4. RFID middleware

RFID middleware is "system software that collects a large volume of raw data from heterogeneous RFID environments, filters them and summarizes into meaningful information, and delivers the information to application services" [38]. Middleware software has the function of managing the flow of data and sending them to back-end management systems.

2.2.3. Advantages of RFID

An advanced automatic identification system based on RFID has several advantages over other data capturing technologies such as a bar coding system.

(1) The visibility provided by the RFID system allows for an accurate knowledge on the inventory level by eliminating conflicts between physical inventory and recorded inventory.

(2) RFID reduces the source of errors by eliminating some of the human interaction in the process. This reduces the labor costs, the inventory inaccuracies, and simplifies the business as a whole.

(3) RFID provides higher security because each tag is extremely unique and almost impossible to duplicate [40].

(4) RFID has higher durability because that the container of bar codes, which are usually paper products or hard metals, exposes them to harsh environments and makes them vulnerable.

2.2.4. Application of RFID in transportation system

The RFID market is already a multimillion dollar industry and the applications of smart chip technologies are limitless. A wide range of emerging applications in the

RFID field are being improved by RFID such as: identification of passports at port of entry, tracking baggage, tracking people in a secure environment, animal identification, health care and usage at public facilities (libraries and transportation).

The transportation system, which requires a high level of accurate and reliable tracking information, is a preeminent field which allows RFID technology to showcase its advantages. Compared to other data capture technology, RFID is more efficient with higher accuracy and security for inspection and tracking purposes. RFID can increase substantially the accuracy of current location data as well as the carrier name and unit number. This ability enables RFID system to perform real time surveillance which allows fleet data capture and also improves transportation process efficiency.

The applications of RFID system in transportation are usually used for traffic management such as toll road RFID system, public transit (such as bus, subway and rail) RFID system, and Car-sharing service RFID system.

2.3.   Previous research of CVISN project

Nebraska has currently attained Commercial Vehicle Information systems and Networks (CVISN) Core Compliance. Nebraska Department of Motor Vehicles (NEDMV) is the lead agency with the Motor Carrier Services Division the primary contact. CVISN project requests NEDMV to perform a stakeholder analysis on utilizing Radio Frequency Identification (RFID) license plates to assist with CVISN objectives at roadside. The project also requires cooperation between the University

of Nebraska (Transportation Center and Radio Frequency Supply Chain Logistics (RfSCL) lab), the NEDMV, the Nebraska Department of Roads (NDOR), The Nebraska Department of Corrections, Cornhusker State Industries (CSI) and the Nebraska State Patrol (NSP)) to perform stakeholder analysis, RFID license plate prototype testing, software and database security testing, and a return on investment analysis in comparison to other technologies.

This program aims to offset the costs of conducting a feasibility study on RFID embedded license plates that may ultimately be expanded for national use. The goal of this program is to investigate the variability of embedding RFID tags into license plates so that strategically located readers alongside streets and roads within the state can capture tag information, and finally select a most valuable RFID system to embed into license plates of the whole nation.

Previous studies have worked on stakeholder analysis. First, questionnaires were designed and stakeholders' requirements were collected during the kickoff meeting. Second, for each stakeholder House of Quality (HOQ) analysis was performed to evaluate the technical requirements. Finally, a ranking of technical requirements was tallied.

Six technical requirements were highlighted to be the most significant to the implementation of RFID system over the national wide. They were separately RFID tag (transponder) reader distance, physical limitation, read rate, display relevant information, RFID tag number, and manufacturing cost. Then considering special customer concerns of each stakeholder, questionnaires were designed aiming at

collecting stakeholders' requirements according to the technical requirements.

Once the stakeholders' requirements were gathered, HOQ analyses were implemented, from which the ordinal ranking of the six technical requirements were gained for each stakeholder. Basically, we had the tally results of the technical requirements as in Table 2.3.

Table 2.3. Relative priorities of individual stakeholder of CVISN project scenario

Criteria	Stakeholder					
	CED	CSI	DMV	NDR-ITS	NDR-Tr	NSP
A	0.16	0.2	0.03	0.03	0.23	0.2
B	0.1	0.21	0.09	0.03	0.23	0.12
C	0.17	0.1	0.03	0.06	0.09	0.18
D	0.23	0.21	0.38	0.37	0.22	0.19
E	0.3	0.08	0.38	0.45	0.22	0.28
F	0.04	0.21	0.09	0.06	0.02	0.03

Further studies will focus on the decision making analysis of different RFID systems, which calls for a comprehensive ranking of the six technical requirements concerning every stakeholders' priorities. For this decision making problem, stakeholders are decision makers, and technical requirements are multiple criteria, based on which the best alternative RFID system will be chosen.

CHAPTER 3. RESEARCH QUESTIONS

3.1. Need for Research

Previous CVISN research systemically chose six technical requirements which were the most important to the implementation of RFID systems. In addition, previous research built House of Quality analysis for these technical requirements according to the customer requirements of each stakeholder. As a result, these technical requirements were tallied respectively by different stakeholders. Future research concentrates on choosing the best RFID system according to these technical requirements. In this decision making problem, technical requirements are playing the role of multiple criteria, which are the crucial keys to solving this problem. Previous research developed the rankings of the criteria by each stakeholder, who are the decision makers in this decision making problem. These separate scores represent only the priorities of the individual stakeholders, which are not general enough to be utilized in the final decision making. Consequently, a comprehensive ranking of these criteria needs to be prudentially decided.

Classical AHP is thought to be a robust way to solve determined decision making problem. However, it neglects the uncertainty and vagueness caused by subjective preference of decision maker in criteria scoring. Accordingly, fuzzy AHP was used to improve this situation.

For the CVISN project, there are six decision makers who had the equal power to contribute to the final decision. Although classical multiple decision makers AHP approach could solve this problem, its pairwise comparison value seems not strong

enough to cover most decision makers' options. This is because that there are too many decision makers and the comparison value for classical AHP is constant. Therefore, this research builds a fuzzy AHP scenario for CVISN project by assuming that the weights of the criteria given by different decision makers are possible weights given by a fictitious decision maker. In this way, this multiple decision maker problem is turned into a one decision maker with a range of comparison values problem, which can be solved by fuzzy AHP approach. Whether or not fuzzy AHP approach is suitable for this situation is then considered.

To verify the applicability of fuzzy AHP to this specified problem, the research first compares classical AHP and fuzzy AHP with a series of random data. The comparison is then used as critical models. By calculating prediction intervals for each individual outcome, the fuzzy AHP approach results of CVISN project are judged. If the results are within the prediction intervals, it tells that fuzzy AHP is appropriate; otherwise, it is not appropriate to this specified problem, and the results of classical AHP is accepted.

3.2. Overall Research Objective

This research is a pilot study for further research of the CVISN project. The overall research objective is to provide a comprehensive rank of the six significant technical requirements, which is the basic criterion for further RFID system chosen.

The methods used in this research are both fuzzy AHP and classical AHP approaches, and results given by the more proper one will be the final rank.

3.3.   Specific Objectives

The main goal of this research will be reached by meeting the following specific

objectives.

SO#1 Compare classical AHP and fuzzy AHP approaches with randomly

generated data to seek for the relationship between the hypothetic potential factors

and the differences of the two approaches' outcomes by building statistical models.

SO#2 Compute the ranking of six significant technical requirements for CVISN

project by both classical AHP and fuzzy AHP approaches.

SO#3 Evaluate the results of SO#2 determining whether or not each outcome is

within the prediction interval on the basis of the critical models given by SO#1. If the

results given by fuzzy AHP approach are appropriate, select them; otherwise, select

results given by classical AHP approach. Finally, the overall ranking of the six

significant technical requirements is given by the verified method.

3.4.   Hypothesis Statements

This research proposes that the differences between classic AHP and fuzzy AHP

are raised by two potential factors. One, it has been illustrated by previous studies that

if the weight of one criterion is weaker than the weights of the others, fuzzy AHP may

give extreme factor weight to this criterion such as zero [5]. This situation does not

happen to classical AHP. So this paper takes the pairwise comparison of one criterion

over another given by AHP as a factor. Two, fuzzy AHP can provide the decision

makers with flexible value options which are in-between a certain range, rather than

deterministic value options. This gives an advantage over classic AHP in solving fuzzy problems. The range of the fuzzy number for pairwise comparison is hence the second factor. In this paper, the influences of these two factors are evaluated.

In conclusion, there are two hypotheses in this research. First, we hypothesize that two factors affect the difference between the outcomes given by classical AHP and fuzzy AHP approaches, which are the pairwise comparison of one criterion over another given by AHP and the range of the fuzzy number for pairwise comparison given by fuzzy AHP. Second, we hypothesize that fuzzy AHP approach is suitable for CVISN project and it provides decision makers with more effective and accurate assistance for selecting RFID system. It is envisioned that, taking into all stakeholders' preferences, fuzzy AHP provides a more comprehensive ranking of the six significant technical requirements for CVISN project.

CHAPTER 4. METHOD

4.1. Rationale of AHP approach, fuzzy AHP approach and prediction intervals

This research uses both classical AHP approach and Chang's extent fuzzy AHP approach as the basic methodologies to find the criteria weights of the multiple decision making problem for CVISN project. Then prediction intervals are used as a judgment to evaluate weight results gained by fuzzy AHP approach compared with classical AHP approach.

4.1.1. AHP approach

Let n be the number of criterion and $z_1, z_2, \ldots, z_n$ be their corresponding relative priority given by one decision maker. Then the judgment matrix A which contains pairwise comparison value a_{ij} for all i, j $\in$ {1,2,…,n} is given by (1).

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} = \begin{bmatrix} 1 & z_1/z_2 & \cdots & z_1/z_n \\ z_2/z_1 & 1 & \cdots & z_2/z_n \\ \vdots & \vdots & \ddots & \vdots \\ z_n/z_1 & z_n/z_2 & \cdots & 1 \end{bmatrix} \qquad (1)$$

For multiple decision makers, let h be the number of decision maker and a_{ij}^{k} be the pairwise comparison value of criteria i and j given by decision maker k, where k = 1, 2, …, h. Then by using geometric mean of the a_{ij}^{k} conducted by each decision maker, we have a new judgment matrix with element given by (2).

$$a_{ij} = (a_{ij}^{1} * a_{ij}^{2} * \ldots * a_{ij}^{k} * \ldots * a_{ij}^{h})^{1/h} = (\Pi_{k=1}^{h} a_{ij}^{k})^{1/h} \qquad (2)$$

The basic procedure for AHP approach by the mean of normalized values method is given as following:

(1) Normalize each column to get a new judgment matrix A'.

$$A' = \begin{bmatrix} a_{11}' & a_{12}' & \cdots & a_{1n}' \\ a_{21}' & a_{22}' & \cdots & a_{2n}' \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1}' & a_{n2}' & \cdots & a_{nn}' \end{bmatrix} = \begin{bmatrix} a_{11}/\sum\limits_{i=1}^{n} a_{i1} & a_{12}/\sum\limits_{i=1}^{n} a_{i2} & \cdots & a_{1n}/\sum\limits_{i=1}^{n} a_{in} \\ a_{21}/\sum\limits_{i=1}^{n} a_{i1} & a_{22}/\sum\limits_{i=1}^{n} a_{i2} & \cdots & a_{2n}/\sum\limits_{i=1}^{n} a_{in} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1}/\sum\limits_{i=1}^{n} a_{i1} & a_{n2}/\sum\limits_{i=1}^{n} a_{i2} & \cdots & a_{nn}/\sum\limits_{i=1}^{n} a_{in} \end{bmatrix} \quad (3)$$

where $\sum\limits_{i=1}^{n} a_{ij}$ is the sum of column j of judgment matrix A.

(2) Sum up each row of normalized judgment matrix A' to get weight vector V.

$$V = \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{bmatrix} = \begin{bmatrix} \sum\limits_{j=1}^{n} a_{1j}' \\ \sum\limits_{j=1}^{n} a_{2j}' \\ \vdots \\ \sum\limits_{j=1}^{n} a_{nj}' \end{bmatrix} \quad (4)$$

(3) Define the final normalization weight vector W.

$$W = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix} = \begin{bmatrix} v_1/\sum\limits_{i=1}^{n} v_i \\ v_2/\sum\limits_{i=1}^{n} v_i \\ \vdots \\ v_n/\sum\limits_{i=1}^{n} v_i \end{bmatrix} \quad (5)$$

4.1.2. Chang's extent fuzzy AHP approach

Like classical AHP approach, fuzzy AHP also has a judgment matrix, using triangle fuzzy number (TFN) instead of constant pairwise comparison value. Let $\tilde{A}$ represent the n*n-judgment matrix containing TFN $\tilde{a}_{ij}$ for all i, j ∈ {1,2,…,n} , as shown in (6).

$$\tilde{A} = \begin{bmatrix} (1,1,1) & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ \tilde{a}_{21} & (1,1,1) & \cdots & \tilde{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \cdots & (1,1,1) \end{bmatrix} \quad (6)$$

where $\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij})$ with l_{ij} is the lower and u_{ij} is the upper limit and m_{ij} is the most

likely value, where we use the geometric mean of l_{ij} and u_{ij} in this paper. So

$m_{ij} = \sqrt{l_{ij} * u_{ij}}$.

Assume that $\tilde{M}_1$ and $\tilde{M}_2$ are two triangular fuzzy numbers with $\tilde{M}_1 = (l1, m1,$

u1) and $\tilde{M}_2 = (l2, m2, u2)$. The basic operations are given by (7)~(9).

$$\tilde{M}_1 \oplus \tilde{M}_2 = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \quad (7)$$

$$\tilde{M}_1 \otimes \tilde{M}_2 = (l_1 l_2, m_1 m_2, u_1 u_2) \quad (8)$$

$$\tilde{M}_1^{-1} = (\frac{1}{u_1}, \frac{1}{m_1}, \frac{1}{l_1}) \quad (9)$$

The basic procedure of Chang's extent fuzzy AHP approach is given as following

[18, 27].

(1) Sum up each row of fuzzy judgment matrix $\tilde{A}$ to get the fuzzy number

vector RS.

$$RS = \begin{bmatrix} rs_1 \\ rs_2 \\ \vdots \\ rs_n \end{bmatrix} = \begin{bmatrix} \sum_{j=1}^{n} \tilde{a}_{1j} \\ \sum_{j=1}^{n} \tilde{a}_{2j} \\ \vdots \\ \sum_{j=1}^{n} \tilde{a}_{nj} \end{bmatrix} = \begin{bmatrix} (\sum_{j=1}^{n} l_{1j}, \sum_{j=1}^{n} m_{1j}, \sum_{j=1}^{n} u_{1j}) \\ (\sum_{j=1}^{n} l_{2j}, \sum_{j=1}^{n} m_{2j}, \sum_{j=1}^{n} u_{2j}) \\ \vdots \\ (\sum_{j=1}^{n} l_{nj}, \sum_{j=1}^{n} m_{nj}, \sum_{j=1}^{n} u_{nj}) \end{bmatrix} \quad (10)$$

(2) Normalize the row fuzzy number vector RS to get the fuzzy synthetic extent value vector S.

$$
\tilde{S}=\begin{bmatrix} \tilde{s}_1 \\ \tilde{s}_2 \\ \vdots \\ \tilde{s}_n \end{bmatrix}=\begin{bmatrix} rs_1 \otimes (\sum_{j=1}^{n} rs_j)^{-1} \\ rs_2 \otimes (\sum_{j=1}^{n} rs_j)^{-1} \\ \vdots \\ rs_n \otimes (\sum_{j=1}^{n} rs_j)^{-1} \end{bmatrix} \qquad (11)
$$

where $(\sum_{j=1}^{n} rs_j)^{-1}$ is the derivative of the sum of the fuzzy number vector RS and it is

calculated by (12).

$$
(\sum_{j=1}^{n} rs_j)^{-1}=(\frac{1}{\sum_{k=1}^{n}\sum_{j=1}^{n}u_{kj}}, \frac{1}{\sum_{k=1}^{n}\sum_{j=1}^{n}m_{kj}}, \frac{1}{\sum_{k=1}^{n}\sum_{j=1}^{n}l_{kj}},) \quad (12)
$$

(3) Compute the degree of possibility to get the non-fuzzy weight vector V.

$$
V=\begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{bmatrix}=\begin{bmatrix} \min V(\tilde{S}_1 \geq \tilde{S}_k) \\ \min V(\tilde{S}_2 \geq \tilde{S}_k) \\ \vdots \\ \min V(\tilde{S}_n \geq \tilde{S}_k) \end{bmatrix} \qquad (13)
$$

where for element i, the subscript $k \in \{1,2,\ldots,n\}$ and $k \neq i$. Also the degree of

possibility of $\tilde{S}_2 = (l_2, m_2, u_2) \geq \tilde{S}_1 = (l_1, m_1, u_1)$ is obtained by (14).

$$
V(\tilde{S}_2 \geq \tilde{S}_1)=\begin{cases} 1, \text{if } m_2 \geq m_1 \\ 0, \text{if } l_1 \geq u_2 \\ \dfrac{l_1-u_2}{(m_2-u_2)-(m_1 \geq l_1)}, \text{otherwise} \end{cases} \qquad (14)
$$

(4) Define the final non-fuzzy normalization weight vector W.

$$W = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix} = \begin{bmatrix} v_1 / \sum_{i=1}^{n} v_i \\ v_2 / \sum_{i=1}^{n} v_i \\ \vdots \\ v_n / \sum_{i=1}^{n} v_i \end{bmatrix} \qquad (15)$$

4.1.3. Prediction interval principles

Assume a simple linear regression model with one response variable Y and one independent variable X. In general, this model can be written as:

$$Y = \beta_0 + \beta_1 X \qquad (16)$$

where β_0 is the intercept of the regression and β_1 is the slope of X. These parameters can be unbiased as b_0 and b_1 estimated by a series of data set (x_i, y_i), where i indicates the ith number of data set and i$\in$ {1,2,…,n} , where n is the total number of set.

With this regression model, the predicted interval of any single predicted value can be calculated on the basis of a population with n data by the following procedure.

(1) Estimate model parameters.

$$b_1 = \frac{S_{xy}}{S_{xx}} \qquad (17)$$

$$b_0 = \bar{y} - b_1 \bar{x} \qquad (18)$$

where $\bar{x}$ and $\bar{y}$ are the means of the two variables, and $\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i$, $\bar{y} = \frac{1}{n} \sum_{i=1}^{n} y_i$.

$$S_{xy} = \sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y}) = \sum_{i=1}^{n} x_i y - \frac{\sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{n} \qquad (19)$$

$$S_{xx} = \sum_{i=1}^{n}(x_i - \overline{x})^2 = \sum_{i=1}^{n} x_i^2 - \frac{(\sum_{i=1}^{n} x_i)^2}{n} \qquad (20)$$

(2) Calculate the predicted value $\hat{Y}$ for all i.

$$\hat{y}_i = b_0 + b_1 x_i \qquad (21)$$

(3) Calculate the mean square of error (MSE).

$$\text{MSE} = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad (22)$$

(4) Calculate the mean $\hat{y}_k$ of a single independent variable x_k.

$$\hat{y}_{at\ x_k} = \overline{y} + b_1(x_k - \overline{x}) \qquad (23)$$

(5) Calculate the variance var($\hat{y}_k$) of the single independent variable x_k.

$$\text{var}(\hat{y}_{at\ x_k}) = \text{MSE}\left[\frac{1}{n} + \frac{(x_k - \overline{x})^2}{\sum_{i=1}^{n}(x_i - \overline{x})^2} + 1\right] \qquad (24)$$

(6) Calculate prediction interval of the single independent variable x_k at confidence level α.

$$\hat{y}_{at\ x_k} \pm t_{\alpha/2,n-2} \sqrt{\mathrm{MSE}\left[\frac{1}{\mathrm{n}} + \frac{(x_k - \overline{x})^2}{\sum\limits_{i=1}^{n}(x_i - \overline{x})^2} + 1\right]} \qquad (24)$$

where $t_{\alpha/2,n-2}$ is the statistic value for t distribution, where n-2 is the degree of freedom. This critical value can be found out at all most every statistic textbook or via internet.

4.2. Research procedure

This research is divided into three scenarios, which are respectively random data scenario, CVISN project scenario, and prediction interval demonstration scenario. The first scenario is running comparison models for classical AHP and fuzzy AHP approaches with randomly generated simulation data to search for the relationship between input variables and output variables so as to give technique supports for the following two parts. The second scenario is dealing with the real multiple-decision problem for CVISN project by both classical AHP and fuzzy AHP approaches. The third scenario is building models with significant input variables and output variables for the CVISN project to check whether the fuzzy AHP approach fits this real problem.

Followings are the detailed procedure of each scenario and the whole research procedure can be demonstrated as a flow chart shown in Figure 4.1.
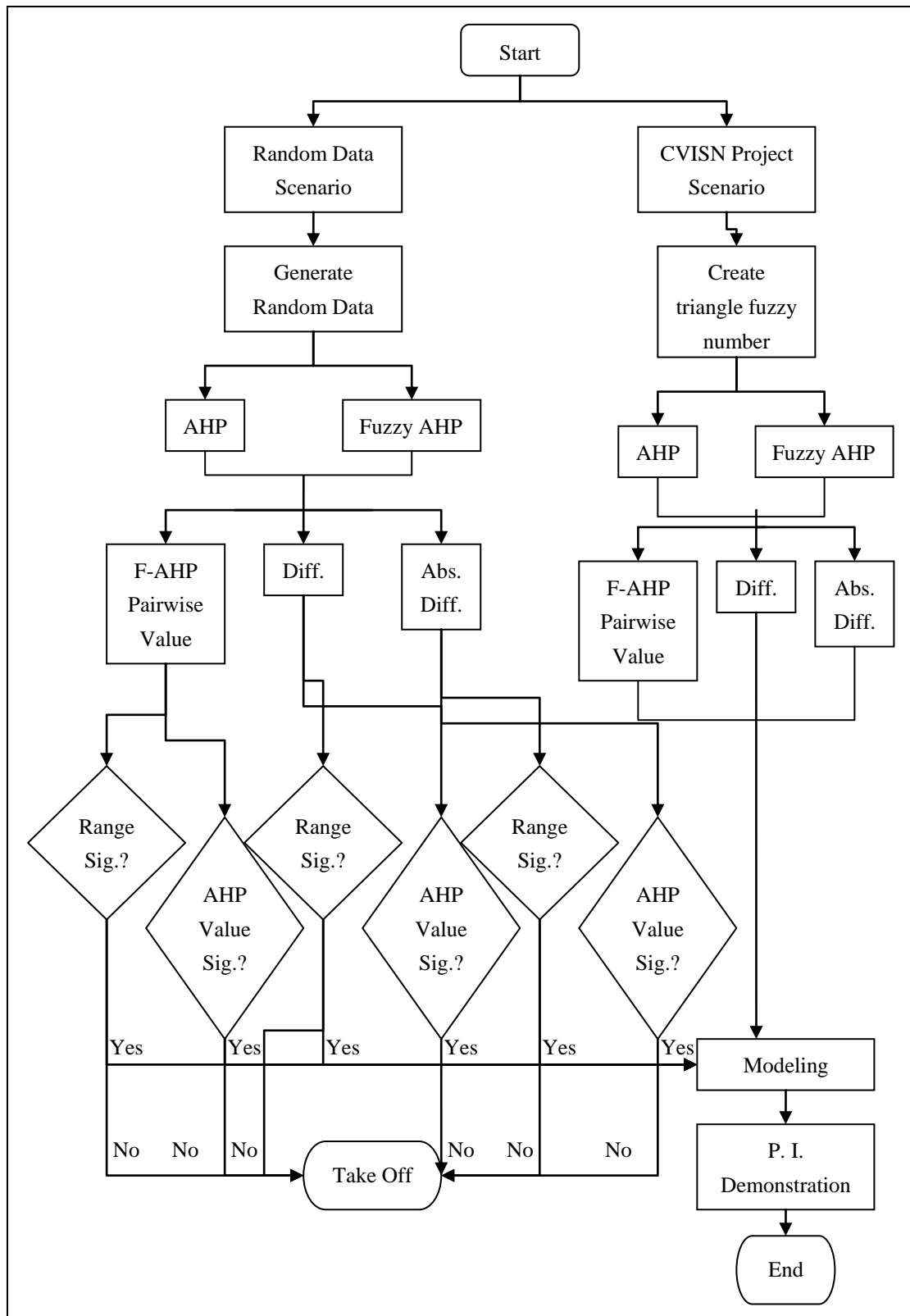
Figure 4.1.   Research procedure

4.2.1. Random data scenario

The following steps are used to generate random data and build benchmark

comparison models between classical AHP and fuzzy AHP approaches.

(1) Generate simulation random data with Excel to represent TFNs for fuzzy
AHP approach.

(2) Calculate weight values for both AHP and fuzzy AHP approaches based on
the data from step 1.

(3) Collect input data, which are range and AHP pairwise weight values, as well
as output data, which includes fuzzy AHP pairwise weight values, difference
of the pairwise weight values between the two approaches, and absolute
difference of pairwise weight values between the two approaches, for
modeling.

(4) Built six models for each pair of input and output data.

(5) Check whether the input variables are significant or not to the each output
variable.

(6) If the input variable is significant, find the relationship between it and the
output variables; otherwise take it off.

4.2.2. CVISN project scenario

The following steps are used to apply both classical AHP and fuzzy AHP to
CVISN project and obtain the final weight vectors.

(1) Analysis previous CVISN project data and denote the multiple decision
making problem.

(2) Create TFNs for fuzzy AHP approach by house of quality from previous
research.

(3) Calculate weight values for both AHP and fuzzy AHP approaches based on the data from step 1.

(4) Collect input and output data for modeling.

(5) Build models with output variables and input variables which have been proved significant in step 5 of random data scenario.

4.2.3. Prediction interval demonstration *scenario*

The following three steps are verify the outcomes of CVISN project, using benchmark comparison models.

(1) For every model in step 5 of CVISN project scenario, calculate prediction interval for each single output value based on the modeling data from step 6 of random data scenario.

(2) Check whether the output values are in-between their corresponding prediction intervals.

(3) If the output values are in-between the prediction intervals, it proves that the fuzzy AHP is appropriate for CVISN project; otherwise use classic AHP approach to solve this problem.

4.3. Analysis plan

Analysis plan gives the explanation of input and output variables, detailed analysis steps, as well as final models for each scenario.

4.3.1. Random data scenario

4.3.1.1 Basic assumption

This set uses random data to represent the totally arbitrary decision makers'

preferences when weighing pairwise criteria. Excel® is used in the generation of the random data as well as the simulation.

The following assumptions are made before conducting the simulation and modeling:

(1) Four criteria and one decision maker are considered in this research to simplify the model;

(2) Random data are generated to represent the TFNs for each pair of criteria, given by the decision maker with totally arbitrary preference;

(3) In order to make the simulation more reasonable and common, the random data are generated from 0 to 10, with the higher value reflecting the stronger importance of one criterion over another and lower value reflecting the weaker importance of one criterion over another. This makes the simulation make sense according to the standard preference scales of pairwise comparison used for classical AHP approach ;

(4) In order to weigh the comparison more fairly, each random data has the probability between (0, 1) equal to 0.5 and the probability between (1, 10) equal to 0.5. In this way, for instance, the importance of criterion A over another one B has the same chance to be larger than one and to be smaller than one, which means that criterion A has the same chance to be more important than B and less important than B;

(5) Geometric mean is used to gain the AHP pairwise values from the TFNs;

(6) All TFNs and AHP pairwise values, including both a_{ij} and its corresponding

reciprocal a_{ji}, are taken into statistic analysis for the final comparison.

4.3.1.2 Notation

The following notations are used to represent different parameters.

i, j: the subscript for criterion i and criterion j. Since there are four criteria in this research simulation, i, j = 1, 2, 3, 4;

$\tilde{a}_{ij}$: TFN for criterion i over criterion j of fuzzy AHP approach;

a_{ij} : pairwise comparison value for criterion i over criterion j of AHP approach;

W_F^T : Final weight values vector of fuzzy AHP approach;

W_A^T : Final weight values vector of AHP approach;

VF_{ij} (V-F in short): pairwise weight value for criterion i over criterion j of fuzzy AHP approach;

VA_{ij} (V-A in short): pairwise weight value for criterion i over criterion j of AHP approach;

R_{ij} (R in short): The range of fuzzy number for criterion i over criterion j of fuzzy AHP approach;

$Diff_{ij}$ (D in short): Difference of the pairwise weight value for criterion i over criterion j between Fuzzy AHP approach and AHP approach, and

$ABS\text{-}Diff_{ij}$ (ABS-D in short): Absolute difference of pairwise weight value for criterion i over criterion j between fuzzy AHP approach and AHP approach.

4.3.1.3 Analysis step

The section of analysis step shows the specific steps of calculation.

(1) For each pairwise comparison of criteria i and j, two random data, r_{ij1} and r_{ij2},

are created, with the meaning of the importance of criterion i over criterion j

(i, j = 1, 2, 3, 4);

(2) For fuzzy AHP approach, $\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij})$ is then formed by l_{ij} = minimum (r_{ij1}, r_{ij2}), m_{ij} = geometric mean (r_{ij1}, r_{ij2}) and u_{ij} = maximum (r_{ij1}, r_{ij2});

(3) For classical AHP approach, a_{ij} = geometric mean (r_{ij1}, r_{ij2});

(4) The importance of criterion j over criterion i for each approach is then given by $\tilde{a}_{ji} = 1/\tilde{a}_{ij} = (1/u_{ij}, 1/m_{ij}, 1/l_{ij})$ and $a_{ji} = 1/a_{ij}$;

(5) Calculation results by using Chang's extent fuzzy AHP approach and classical AHP approach are two vectors of weights $W_F^T = (WF_1, WF_2, WF_3, WF_4)$ and $W_A^T = (WA_1, WA_2, WA_3, WA_4)$;

(6) Pairwise weight values between criterion i and criterion j for the two approaches are computed by $VF_{ij} = WF_i/WF_j$ and $VA_{ij} = WA_i/WA_j$;

(7) Range of pairwise TFNs of Fuzzy AHP for criterion i over criterion j is given by $R_{ij} = u_{ij} - l_{ij}$, and

(8) Difference and absolute difference of pairwise weight values are then calculate by $Diff_{ij} = VF_{ij} - VA_{ij}$ and $ABS\text{-}Diff_{ij}$ = absolute $(Diff_{ij})$.

4.3.1.4 Data collection

The following parts are used for data generation and specification.

(1) Generate initial data: a series of 240 data are generated randomly, and then another 240 accordingly reciprocal data are calculated. Since two random data are necessary to represent one pairwise comparison value, these 480 data are used to form 240 sets of pairwise comparison values for both fuzzy AHP

and AHP, including 20 groups of scenarios, each of which contains 12

pairwise comparison values (since there are 4 criteria).

(2) Calculate statistic model data: calculate the following five variable values

group by group: V-A, R, V-F, D, and ABS-D, the first two of which are input

random variables for the modeling and the last three are output variables.

(3) In order to analyze the variables' effects more specifically, the data are

divided into two subgroups, one includes 120 series of data with comparison

weight values given by AHP approach greater than 1 and the other group

includes the left 120 series of data with comparison weight values given by

AHP approach smaller than 1. To distinguish them, this research describes

every parameter in the first group with subscript 1 and the second group with

subscript 2. In this way, there are 6 models in total.

4.3.1.5 Demonstrated sample calculation and procedure

This set gives the data collection and calculation procedure for one of the 24

group scenarios as a demonstrated sample.

(1) Let A, B, C, D represent the four criteria of the first group scenario.

(2) Generate two random data r_{ij1} and r_{ij2} for each pairwise comparison values of

criterion i over criterion j, so there are totally 12 data for the six pariwise

comparison, as shown in Table 4.1.

Table 4.1. Pairwise comparison values for group one scenario of random dara scenario

Series	Pairwise	Random Data		Fuzzy AHP ($\tilde{a}_{ij}$)			AHP (a_{ij})
No.	Comparison	r_{ij1}	r_{ij2}	l_{ij}	m_{ij}	u_{ij}	a_{ij}
1	A/B	3.962	5.005	3.962	4.453	5.005	4.453
2	A/C	3.276	6.886	3.276	4.749	6.886	4.749

3	A/D	1.140	0.165	0.165	0.433	1.140	0.433
4	B/C	2.688	0.120	0.120	0.569	2.688	0.569
5	B/D	9.151	4.923	4.923	6.712	9.151	6.712
6	C/D	0.160	2.059	0.160	0.574	2.059	0.574
7	B/A	0.252	0.200	0.200	0.225	0.252	0.225
8	C/A	0.305	0.145	0.145	0.211	0.305	0.211
9	D/A	0.877	6.075	0.877	2.308	6.075	2.308
10	C/B	0.372	8.307	0.372	1.758	8.307	1.758
11	D/B	0.109	0.203	0.109	0.149	0.203	0.149
12	D/C	6.250	0.486	0.486	1.742	6.250	1.742

(3) Calculate the reciprocals of the 12 data as the pairwise comparison values of criterion j over criterion i, so there are 24 data in total.

(4) Generate judgment matrix A for AHP approach and judgment matrix $\tilde{A}$ with TFNs for fuzzy AHP approach, as shown in Table 4.2 and 4.3.

Table 4.2. Judgment matrix for ahp approach of random dara scenario

Criterion		A	B	C	D
	No.	1	2	3	4
A	1	1.000	4.453	4.749	0.433
B	2	0.225	1.000	0.569	6.712
C	3	0.211	1.758	1.000	0.574
D	4	2.308	0.149	1.742	1.000

Table 4.3. Judgment matrix for fuzzy ahp approach of random dara scenario

Criterion		A	B	C	D
	No.	1	2	3	4
A	1	(1.000,1.000,1.000)	(3.962,4.453, 5.005)	(3.276, 4.749, 6.886)	(0.165, 0.433, 1.140)
B	2	(0.200, 0.225, 0.252)	(1.000,1.000,1.000)	(0.120, 0.569, 2.688)	(4.923, 6.712, 9.151)
C	3	(0.145, 0.211, 0.305)	(0.372, 1.758, 8.307)	(1.000,1.000,1.000)	(0.160, 0.574, 2.059)
D	4	(0.877, 2.308, 6.075)	(0.109, 0.149, 0.203)	(0.486, 1.742, 6.250)	(1.000,1.000,1.000)

(5) For AHP approach, the calculations of final weight vector WT are as following:

- Get a new judgment matrix A'.

$$\sum_{i=1}^{4} a_{i1} = 1+0.225+0.211+2.308 = 3.743,$$

$$\sum_{i=1}^{4} a_{i2} = 7.360, \quad \sum_{i=1}^{4} a_{i1} = 8.060, \quad \sum_{i=1}^{4} a_{i4} = 8.719.$$

$$A' = \begin{bmatrix} a_{11}' & a_{12}' & a_{13}' & a_{14}' \\ a_{21}' & a_{22}' & a_{23}' & a_{24}' \\ a_{31}' & a_{32}' & a_{34}' & a_{34}' \\ a_{41}' & a_{42}' & a_{43}' & a_{44}' \end{bmatrix} = \begin{bmatrix} 0.267 & 0.605 & 0.589 & 0.050 \\ 0.060 & 0.136 & 0.071 & 0.770 \\ 0.056 & 0.239 & 0.124 & 0.066 \\ 0.617 & 0.020 & 0.216 & 0.115 \end{bmatrix} \quad (16)$$

- Get weight vector V.

$$V = \begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ v_4 \end{bmatrix} = \begin{bmatrix} \sum_{j=1}^{4} a_{1j}' \\ \sum_{j=1}^{4} a_{2j}' \\ \sum_{j=1}^{4} a_{3j}' \\ \sum_{j=1}^{4} a_{4j}' \end{bmatrix} = \begin{bmatrix} 1.511 \\ 1.036 \\ 0.485 \\ 0.968 \end{bmatrix} \quad (17)$$

- Get final normalization weight vector W.

$$W = \begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ w_4 \end{bmatrix} = \begin{bmatrix} v_1 / \sum_{i=1}^{4} v_i \\ v_2 / \sum_{i=1}^{4} v_i \\ v_3 / \sum_{i=1}^{4} v_i \\ v_4 / \sum_{i=1}^{4} v_i \end{bmatrix} = \begin{bmatrix} 0.378 \\ 0.259 \\ 0.121 \\ 0.242 \end{bmatrix} \quad (18)$$

(6) For fuzzy AHP approach, the calculations of final weight vector WT are as

following:

- Get fuzzy number vector RS.

$$rs_1 = (\sum_{j=1}^{4} l_{1j}, \sum_{j=1}^{4} m_{1j}, \sum_{j=1}^{4} u_{1j})$$

$= ((1+3.962+3.276+0.165), (1+4.453+4.749+0.433), (1+5.005+6.886+1.140))$

$= (8.403, 10.636, 14.031)$

$$RS = \begin{bmatrix} rs_1 \\ rs_2 \\ rs_3 \\ rs_4 \end{bmatrix} = \begin{bmatrix} (\sum_{j=1}^{4} l_{1j}, \sum_{j=1}^{4} m_{1j}, \sum_{j=1}^{4} u_{1j}) \\ (\sum_{j=1}^{4} l_{2j}, \sum_{j=1}^{4} m_{2j}, \sum_{j=1}^{4} u_{2j}) \\ (\sum_{j=1}^{4} l_{3j}, \sum_{j=1}^{4} m_{3j}, \sum_{j=1}^{4} u_{3j}) \\ (\sum_{j=1}^{4} l_{4j}, \sum_{j=1}^{4} m_{4j}, \sum_{j=1}^{4} u_{4j}) \end{bmatrix} = \begin{bmatrix} (8.403,10.636,14.031) \\ (6.243,8.505,13.092) \\ (1.677,3.543,11.672) \\ (2.472,5.199,13.528) \end{bmatrix} \quad (19)$$

● Get fuzzy synthetic extent value vector S.

$$\sum_{j=1}^{4} rs_j = (8.403, 10.636, 14.031) \oplus (6.243, 8.505, 13.092)$$

$$\oplus (1.677, 3.534, 11.672) \oplus (2.472, 5.199, 13.528)$$

$= (8.403+6.243+1.677+2.472, 10.636+8.505+3.534+5.199,$

$14.031+13.092+11.672+13.528)$

$= (18.794, 27.883, 52.323)$

$$\tilde{s}_1 = rs_1 \otimes (\sum_{j=1}^{4} rs_j)^{-1}$$

$= (8.403, 10.636, 14.031) \otimes (18.794, 27.883, 52.323)^{-1}$

$= (8.403, 10.636, 14.031) \otimes (1/52.323, 1/27.883, 1/52.323)$

$= (8.403/52.323, 10.636/27.883, 14.031/52.323)$

$= (0.161, 0.381, 0.747)$

$$\tilde{S}=\begin{bmatrix} \tilde{s}_1 \\ \tilde{s}_2 \\ \tilde{s}_3 \\ \tilde{s}_4 \end{bmatrix}=\begin{bmatrix} rs_1 \otimes (\sum_{j=1}^{4} rs_j)^{-1} \\ rs_2 \otimes (\sum_{j=1}^{4} rs_j)^{-1} \\ rs_3 \otimes (\sum_{j=1}^{4} rs_j)^{-1} \\ rs_4 \otimes (\sum_{j=1}^{4} rs_j)^{-1} \end{bmatrix}=\begin{bmatrix} (0.161,0.381,0.747) \\ (0.119,0.305,0.697) \\ (0.032,0.127,0.621) \\ (0.047,0.186,0.720) \end{bmatrix} \quad (20)$$

- Get non-fuzzy weight vector V.

$V(\tilde{S}_1 \geq \tilde{S}_2) = 1$, $V(\tilde{S}_1 \geq \tilde{S}_3) = 1$, $V(\tilde{S}_1 \geq \tilde{S}_4) = 1$;

$V(\tilde{S}_2 \geq \tilde{S}_1) = 0.875$, $V(\tilde{S}_2 \geq \tilde{S}_3) = 1$, $V(\tilde{S}_2 \geq \tilde{S}_4) = 1$;

$V(\tilde{S}_3 \geq \tilde{S}_1) = 0.644$, $V(\tilde{S}_3 \geq \tilde{S}_2) = 0.738$, $V(\tilde{S}_3 \geq \tilde{S}_4) = 0.906$;

$V(\tilde{S}_4 \geq \tilde{S}_1) = 0.741$, $V(\tilde{S}_4 \geq \tilde{S}_2) = 0.835$, $V(\tilde{S}_4 \geq \tilde{S}_3) = 1$;

$$V=\begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ v_4 \end{bmatrix}=\begin{bmatrix} \min V(\tilde{S}_1 \geq \tilde{S}_k) \\ \min V(\tilde{S}_2 \geq \tilde{S}_k) \\ \min V(\tilde{S}_3 \geq \tilde{S}_k) \\ \min V(\tilde{S}_4 \geq \tilde{S}_k) \end{bmatrix}=\begin{bmatrix} 1 \\ 0.875 \\ 0.644 \\ 0.741 \end{bmatrix} \quad (21)$$

- Get final non-fuzzy weight vector W.

$$W=\begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ w_4 \end{bmatrix}=\begin{bmatrix} v_1 / \sum_{i=1}^{4} v_i \\ v_2 / \sum_{i=1}^{4} v_i \\ v_3 / \sum_{i=1}^{4} v_i \\ v_4 / \sum_{i=1}^{4} v_i \end{bmatrix}=\begin{bmatrix} 0.307 \\ 0.268 \\ 0.198 \\ 0.227 \end{bmatrix} \quad (22)$$

(7) Collect and calculate input and output variables, which are shown in Table

4.4.

Table 4.4.   Input and output variables of random dara scenario

Subgroup No.	Pairwise Comparison	Input Variable		Output Variable		
		R	V-A	V-F	D	ABS-D
1	A/B	1.043	10.968	6.040	-4.927	4.927
1	A/C	3.610	8.346	2.562	-5.784	5.784
2	A/D	0.975	0.708	0.752	0.045	0.045
2	B/C	2.568	0.761	0.424	-0.337	0.337
2	B/D	4.228	0.065	0.125	0.060	0.060
2	C/D	1.899	0.085	0.294	0.209	0.209
2	B/A	0.052	0.091	0.166	0.074	0.074
2	C/A	0.160	0.120	0.390	0.271	0.271
1	D/A	5.198	1.413	1.329	-0.084	0.084
1	C/B	7.935	1.314	2.358	1.044	1.044
1	D/B	0.094	15.501	8.027	-7.474	7.474
1	D/C	5.764	11.796	3.404	-8.392	8.392

4.3.2. CVISN project scenario

4.3.2.1 Basic assumptions

Previous research of CVISN project built House of Quality (HOQ) for each of the six stakeholders via questionnaires to analyze the importance of six significant technical requirements (which are denoted as capital A to capital F in the following research). The numerical results for the technical requirements from the HOQ are in the form of relative priorities for each stakeholder as seen in the pre-mentioned table in the previous research of CVISN project section of chapter 2.

In order to further analyze the importance of the six technical requirements in a more comprehensive perspective, the following assumptions are made.

(1) The weights for the six stakeholders are the same to each other. This means that they have the equal right to evaluate the technical requirements.

(2) This problem can be considered as a multiple decision maker with multiple criteria decision making problem. In this way, classical AHP approach could

be applied to solve it.

(3) This problem can be considered as a single decision maker with multiple criteria decision making problem. In this way, weights of the six technical requirements given by an individual stakeholder are considered as one possible series of weights given by this fictitious decision maker. So there are six possible series of weights given by the decision maker. Therefore, fuzzy AHP approach could be applied to solve it.

(4) Geometric mean method is applied to calculate the most likely value when obtaining the TFNs of fuzzy AHP approach.

4.3.2.2 Notation

The following notations are used to represent different parameters.

i, j: the subscript for criterion i and criterion j. Since there are six criteria in this research simulation, i, j = 1, 2, 3, 4, 5, 6;

k: the superscript for the kth decision maker for AHP approach. There are six stakeholders, so k = 1, 2, 3, 4, 5, 6;

z_{ik}: relative priority of criterion i given by the kth decision maker;

$\tilde{a}_{ij}$: TFN for criterion i over criterion j of fuzzy AHP approach;

a_{ijk} : pairwise comparison value for criterion i over criterion j given by decision maker k of AHP approach;

W_F^T : Final weight values vector of fuzzy AHP approach;

W_A^T : Final weight values vector of AHP approach;

VF_{ij} (V-F in short): pairwise weight value for criterion i over criterion j of fuzzy

AHP approach;

VA$_{ij}$ (V-A in short): pairwise weight value for criterion i over criterion j of AHP approach;

R$_{ij}$ (R in short): The range of fuzzy number for criterion i over criterion j of fuzzy AHP approach;

Diff$_{ij}$ (D in short): Difference of the pairwise weight value for criterion i over criterion j between fuzzy AHP approach and AHP approach, and

ABS-Diff$_{ij}$ (ABS-D in short): Absolute difference of pairwise weight value for criterion i over criterion j between fuzzy AHP approach and AHP approach.

4.3.1.3 Analysis steps

The section of analysis step shows the specific steps of calculation.

(1) Gain judgment matrix Ak with element a$_{ijk}$ = z$_{ik}$/z$_{jk}$ for each stakeholder by

    (1);

(2) For fuzzy AHP approach, $\tilde{a}_{ij}$ = (l$_{ij}$, m$_{ij}$, u$_{ij}$) is then formed by l$_{ij}$ = minimum

    (a$_{ijk}$), m$_{ij}$ = geometric mean (a$_{ijk}$) and u$_{ij}$ = maximum (a$_{ijk}$), for k = 1~6;

(3) Gain judgment matrix $\tilde{A}$ with TFNs for Fuzzy AHP approach;

(4) For classical AHP approach, a$_{ij}$ = geometric mean (a$_{ijk}$) , for k = 1~6;

(5) Gain new judgment matrix A for AHP approach.

(6) Calculation results by using Chang's extent fuzzy AHP approach and

    classical AHP approach are two vectors of weights W_F^T =(WF$_1$, WF$_2$, WF$_3$,

    WF$_4$) and W_A^T =(WA$_1$, WA$_2$, WA$_3$, WA$_4$);

(7) Pairwise weight values between criterion i and criterion j for the two

approaches are computed by $VF_{ij} = WF_i / WF_j$ and $VA_{ij} = WA_i / WA_j$;

(8) Range of pairwise TFNs of Fuzzy AHP for criterion i over criterion j is given

by $R_{ij} = u_{ij} - l_{ij}$;

(9) Difference and absolute difference of pairwise weight values are then

calculate by $Diff_{ij} = VF_{ij} - VA_{ij}$ and $ABS\text{-}Diff_{ij} = absolute (Diff_{ij})$.

4.3.2.4 Data collection

Table 4.5~4.10 give the judgment matrix given by individual stakeholder. These

are the initial data for the following analysis and calculation, by which the input and

output variables for the modeling could be obtained. For example, the comparison

value of criterion A over criterion B given by CED is calculated based on Table 2.3,

which is 0.16/0.1 = 1.6.

Table 4.5. Judgment matrix given by CED of CVISN project scenario

Criteria	CED					
	A	B	C	D	E	F
A	1.000	1.600	0.941	0.696	0.533	4.000
B	0.625	1.000	0.588	0.435	0.333	2.500
C	1.063	1.700	1.000	0.739	0.567	4.250
D	1.438	2.300	1.353	1.000	0.767	5.750
E	1.875	3.000	1.765	1.304	1.000	7.500
F	0.250	0.400	0.235	0.174	0.133	1.000

Table 4.6. Judgment matrix given by CSI of CVISN project scenario

Criteria	CSI					
	A	B	C	D	E	F
A	1.000	0.952	2.000	0.952	2.500	0.952
B	1.050	1.000	2.100	1.000	2.625	1.000
C	0.500	0.476	1.000	0.476	1.250	0.476
D	1.050	1.000	2.100	1.000	2.625	1.000
E	0.400	0.381	0.800	0.381	1.000	0.381
F	1.050	1.000	2.100	1.000	2.625	1.000

Table 4.7. Judgment matrix given by DMV of CVISN project scenario

Criteria	DMV					
	A	B	C	D	E	F
A	1.000	0.333	1.000	0.079	0.079	0.333
B	3.000	1.000	3.000	0.237	0.237	1.000
C	1.000	0.333	1.000	0.079	0.079	0.333
D	12.667	4.222	12.667	1.000	1.000	4.222
E	12.667	4.222	12.667	1.000	1.000	4.222
F	3.000	1.000	3.000	0.237	0.237	1.000

Table 4.8. Judgment matrix given by NDR-ITS of CVISN project scenario

Criteria	NDR-ITS					
	A	B	C	D	E	F
A	1.000	1.000	0.500	0.081	0.067	0.500
B	1.000	1.000	0.500	0.081	0.067	0.500
C	2.000	2.000	1.000	0.162	0.133	1.000
D	12.333	12.333	6.167	1.000	0.822	6.167
E	15.000	15.000	7.500	1.216	1.000	7.500
F	2.000	2.000	1.000	0.162	0.133	1.000

Table 4.9. Judgment matrix given by NDR-Tr of CVISN project scenario

Criteria	NDR-Tr					
	A	B	C	D	E	F
A	1.000	1.000	2.556	1.045	1.045	11.500
B	1.000	1.000	2.556	1.045	1.045	11.500
C	0.391	0.391	1.000	0.409	0.409	4.500
D	0.957	0.957	2.444	1.000	1.000	11.000
E	0.957	0.957	2.444	1.000	1.000	11.000
F	0.087	0.087	0.222	0.091	0.091	1.000

Table 4.10. Judgment matrix given by NSP of CVISN project scenario

Criteria	NSP					
	A	B	C	D	E	F
A	1.000	1.667	1.111	1.053	0.714	6.667
B	0.600	1.000	0.667	0.632	0.429	4.000
C	0.900	1.500	1.000	0.947	0.643	6.000
D	0.950	1.583	1.056	1.000	0.679	6.333
E	1.400	2.333	1.556	1.474	1.000	9.333
F	0.150	0.250	0.167	0.158	0.107	1.000

4.3.2.5 Demonstrated sample calculation and procedure

This set gives example of calculations and demo-procedure of this senario.

(1) Combine the six judgment matrixes given by different stakeholders together

to gain pairwise comparison values for both classical AHP and fuzzy AHP

approaches. Table 4.11 shows the half of the pairwise comparison values, the

other half should be the reciprocals of these values.

Table 4.11. Pairwise comparison values of CVISN project scenario

Pairwise Comparison	Stakeholder						Fuzzy AHP ($\tilde{a}_{ij}$)			AHP
	CED	CSI	DMV	NDR-ITS	NDR-Tr	NSP	l_{ij}	m_{ij}	u_{ij}	a_{ij}
A/B	1.600	0.952	0.333	1.000	1.000	1.667	0.333	0.973	1.667	0.973
A/C	0.941	2.000	1.000	0.500	2.556	1.111	0.500	1.178	2.556	1.178
A/D	0.696	0.952	0.079	0.081	1.045	1.053	0.079	0.409	1.053	0.409
A/E	0.533	2.500	0.079	0.067	1.045	0.714	0.067	0.417	2.500	0.417
A/F	4.000	0.952	0.333	0.500	11.500	6.667	0.333	1.911	11.500	1.911
B/C	0.588	2.100	3.000	0.500	2.556	0.667	0.500	1.211	3.000	1.211
B/D	0.435	1.000	0.237	0.081	1.045	0.632	0.081	0.420	1.045	0.420
B/E	0.333	2.625	0.237	0.067	1.045	0.429	0.067	0.428	2.625	0.428
B/F	2.500	1.000	1.000	0.500	11.500	4.000	0.500	1.965	11.500	1.965
C/D	0.739	0.476	0.079	0.162	0.409	0.947	0.079	0.347	0.947	0.347
C/E	0.567	1.250	0.079	0.133	0.409	0.643	0.079	0.354	1.250	0.354
C/F	4.250	0.476	0.333	1.000	4.500	6.000	0.333	1.622	6.000	1.622
D/E	0.767	2.625	1.000	0.822	1.000	0.679	0.679	1.019	2.625	1.019
D/F	5.750	1.000	4.222	6.167	11.000	6.333	1.000	4.674	11.000	4.674
E/F	7.500	0.381	4.222	7.500	11.000	9.333	0.381	4.585	11.000	4.585

(2) Generate judgment matrix A for AHP approach and judgment matrix $\tilde{A}$

with TFNs for fuzzy AHP approach, as shown in table 4.12 and 4.13.

Table 4.12. Judgment matrix for AHP approach of CVISN project scenario

Criterion	A	B	C	D	E	F
A	1.000	0.973	1.178	0.409	0.417	1.911
B	1.028	1.000	1.211	0.420	0.428	1.965
C	0.849	0.826	1.000	0.347	0.354	1.622
D	2.446	2.379	2.882	1.000	1.019	4.674
E	2.399	2.334	2.827	0.981	1.000	4.585
F	0.523	0.509	0.616	0.214	0.218	1.000

Table 4.13. Judgment matrix for fuzzy AHP approach of CVISN project scenario

Criterion	A	B	C	D	E	F
A	(1.000,1.000,1.000)	(0.333,0.973,1.667)	(0.500,1.178,2.556)	(0.079,0.409,1.053)	(0.067,0.417,2.500)	(0.333,1.911,11.500)
B	(0.600,1.028,3.000)	(1.000,1.000,1.000)	(0.500,1.211,3.000)	(0.081,0.420,1.045)	(0.067,0.429,2.625)	(0.500,1.965,11.500)

C	(0.391,0.849,2.000)	(0.333,0.826,2.000)	(1.000,1.000,1.000)	(0.079,0.347,0.947)	(0.079,0.354,1.250)	(0.333,1.622,6.000)
D	(0.950,2.446,12.667)	(0.957,2.379,12.333)	(1.056,2.882,12.667)	(1.000,1.000,1.000)	(0.679,1.019,2.625)	(1.000,4.674,11.000)
E	(0.400,2.399,15.000)	(0.381,2.334,15.000)	(0.800,2.827,12.667)	(0.381,0.981,1.474)	(1.000,1.000,1.000)	(0.381,4.585,11.000)
F	(0.087,0.523,3.000)	(0.087,0.509,2.000)	(0.167,0.616,3.000)	(0.091,0.214,1.000)	(0.091,0.218,2.625)	(1.000,1.000,1.000)

(3) The following procedures to compute the final weight vector W_A for AHP

approach and non-fuzzy weight vector W_F for fuzzy AHP approach are

totally the same as previous steps for random data scenario part.

$$W_A = \begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ w_4 \\ w_5 \\ w_6 \end{bmatrix} = \begin{bmatrix} 0.121 \\ 0.125 \\ 0.103 \\ 0.297 \\ 0.291 \\ 0.063 \end{bmatrix} \quad (23)$$

$$W_F = \begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ w_4 \\ w_5 \\ w_6 \end{bmatrix} = \begin{bmatrix} 0.165 \\ 0.167 \\ 0.147 \\ 0.191 \\ 0.189 \\ 0.142 \end{bmatrix}$$

4.3.3. Prediction interval demonstration secario

The following five steps are used to specify the procedure of prediction interval

part.

(1) Assume the confidence level α=0.05 for this research.

(2) The six simple linear regression models for each combination of input and

output variables obtained in random data scenario part are used to illustrate

the relationship of these variables and to predict the single response variables

in the CVISN project scenario part.

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(3) Prediction intervals for every single response variables in each model are calculated based on the six models.

(4) Check whether or not the actual response values of the CVISN project that are attained by fuzzy AHP approach are in-between the predicted intervals.

(5) Since all of these calculations in this part are based on the previous two parts, detailed calculations will be posted later in the result chapter.

CHAPTER 5. RESULTS

5.1. Random data scenario

A series of linear regression models are built with SPSS statistic software to seek

the relationship between different dependent variables and the two factors: V-A and R.

Three variables V-F, D, and ABS-D, are evaluated as dependent variables with respect

to the two factors. For each pair of input variables and one output variable, one model

is built. In addition, the 120 pairs of comparison weight values are divided into two

parts, one of which contains values less than 1 and other one contains values larger

than 1. Therefore, there are 6 models in total.

5.1.1. Model 1: V-F1 vs R1 and V-A1

The independent parameters of the first model are R1 and V-A1 and the

predicted parameter is V-F1.

5.1.1.1. Data base for this model is shown in Figure 5.1.

Figure 5.1 shows the independent and predicted parameters of model 1. It shows

the visual examination of the relationship between these parameters.
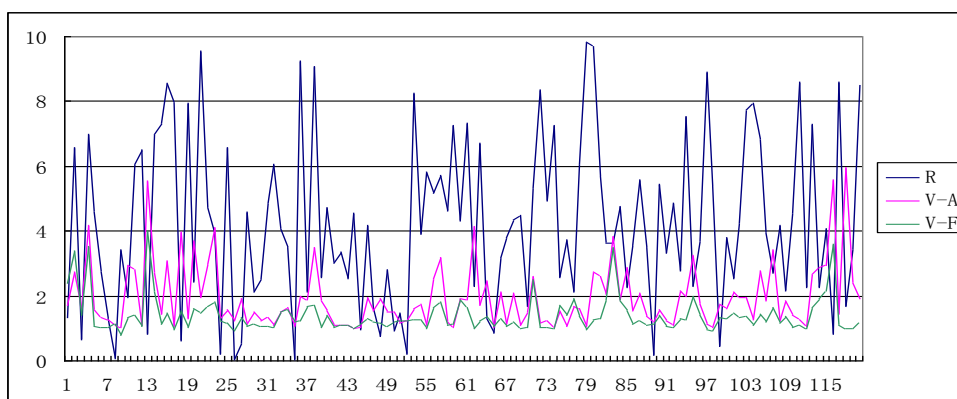

Figure 5.1.   Data base for model 1.

5.1.1.2. SPSS output

Table 5.1 and 5.2 shows the ANOVA and coefficient table. Useful information of

the output includes Mean Square of Error/Residual (MSE) from ANOVA table, the

coefficients and the significant of each independent parameter from coefficient table.

Table 5.1. ANOVA table for model 1

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	16.441	2	8.221	45.727	.000
Residual	21.034	117	.180		
Total	37.475	119			

Table 5.2. Coefficient table for model 1

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	S.E. [a]	Beta		
Const.	.687	.110		6.248	.000
R1	-2.331E-03	.015	-.011	-.155	.877
V-A1	.372	.039	.661	9.522	.000

a.   Standard Error

5.1.1.3 Numerical model

Since the significance for R1 is 0.877, which is larger than the α level (0.05), it is

not significant to the dependent variable V-F1, which means that it has no influence to

V-F1. Also from the coefficient table it is easy to see that the coefficient of

independent parameter V-A1 is 0.372 and the coefficient of the constant parameter is

0.687, as a result, the model for V-F1 is presented as: V-F1 = 0.687 + 0.372 V-A1.

5.1.2. Model 2: D1 vs R1 and V-A1

The independent parameters of the first model are R1 and V-A1 and the

predicted parameter is D1.

5.1.2.1. Data base for this model is shown in Figure 5.2.

Figure 5.2 shows the independent and predicted parameters of model 2. It shows

the visual examination of the relationship between these parameters.

Figure 5.2.   Data base for model 2.

5.1.2.2. SPSS output

Table 5.3 and 5.4 shows the ANOVA and coefficient table.

Table 5.3.   ANOVA table for model 2

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	46.503	2	23.252	129.337	.000
Residual	21.034	117	.180		
Total	67.537	119			

Table 5.4.   Coefficient table for model 2

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	S.E. a	Beta		
Const.	.687	.110		6.248	.000
R1	-2.331E-03	.015	-.008	-.155	.877
V-A1	-.628	.039	-.830	-16.05	.000

5.1.2.3. Numerical model

R1 is not significant to D1, so the model for D1 is then presented as: D1 = 0.687

− 0.628 V-A1.

5.1.3.   Model 3: ABS-D1 vs R1 and V-A1

The independent parameters of the first model are R1 and V-A1 and the

predicted parameter is ABS-D1.

5.1.3.1. Data base for this model is shown in Figure 5.3.

Figure 5.3 shows the independent and predicted parameters of model 3. It shows

the visual examination of the relationship between these parameters.
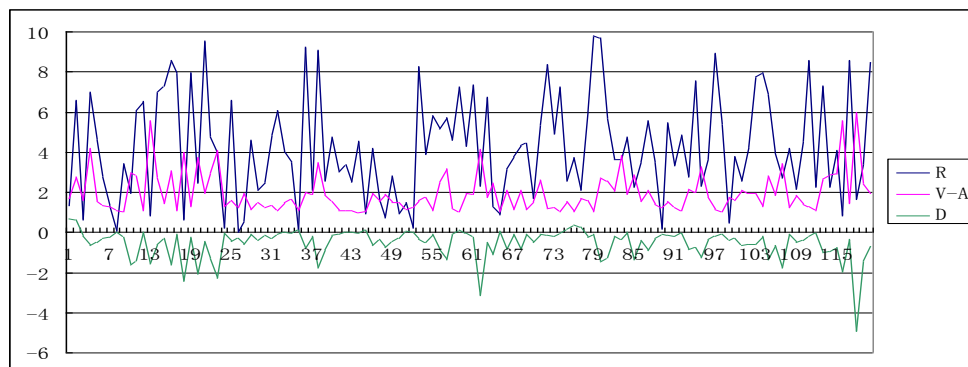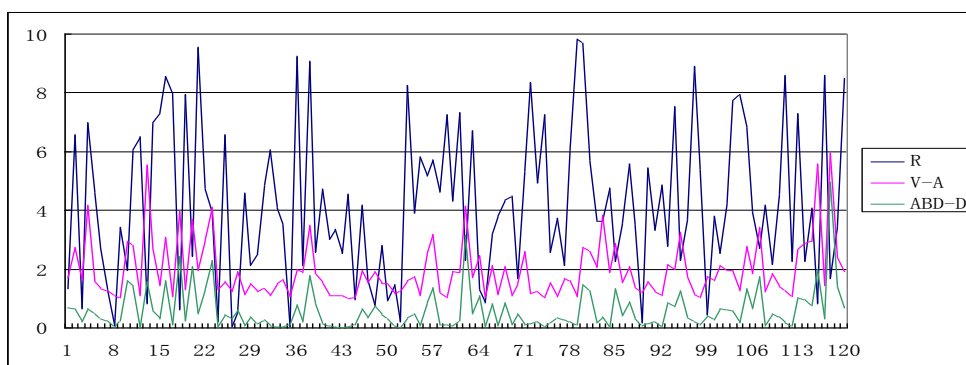

Figure 5.3.   Data base for model 3.

5.1.3.2. SPSS output

Table 5.5 and 5.6 shows the ANOVA and coefficient table.

Table 5.5.   ANOVA table for model 3

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	45.055	2	22.528	160.505	.000
Residual	16.422	117	.140		
Total	61.477	119			

Table 5.6.   Coefficient table for model 3

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	S.E. a	Beta		
Const.	-.591	.097		-6.088	.000
R1	-4.526E-03	.013	-.016	-.342	.733
V-A1	.616	.035	.855	17.83	.000

5.1.3.3. Numerical model

R1 is not a significant parameter to ABS-D1, and the model for ABS-D1 is then

presented as: ABS-D1 = -0.591 + 0.616 V-A1.

5.1.4.   Model 4: V-F2 vs R2 and V-A2

The independent parameters of the first model are R2 and V-A2 and the

predicted parameter is V-F2.

5.1.4.1. Data base for this model is shown in Figure 5.4.

Figure 5.4 shows the independent and predicted parameters of model 4. It shows

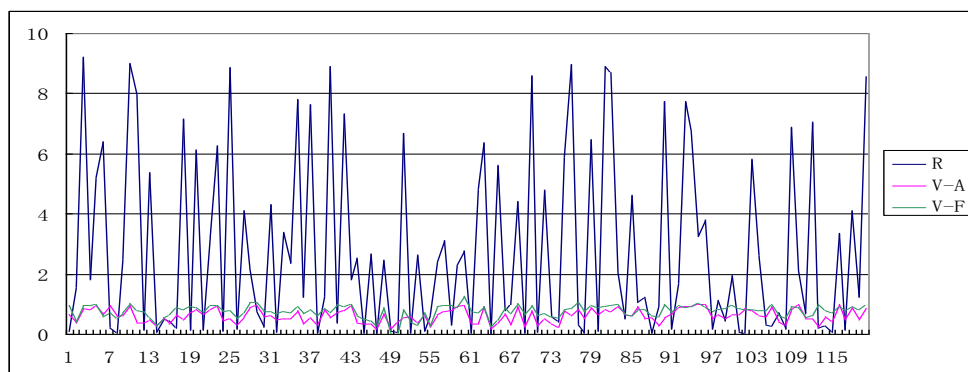the visual examination of the relationship between these parameters.

Figure 5.4.   Data base for model 4.

5.1.4.2. SPSS output

Table 5.7 and 5.8 shows the ANOVA and coefficient table.

Table 5.7. ANOVA table for model 4

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	3.226	2	1.613	77.439	.000
Residual	2.437	117	.021		
Total	5.663	119			

Table 5.8. Coefficient table for model 4

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	S.E. a	Beta		
Const.	.327	.038		8.630	.000
R2	5.596E-03	.005	.076	1.175	.242
V-A2	.688	.062	.724	11.18	.000

5.1.4.3. Numerical model

R2 has only slight influence on V-F2, so the model for V-F2 is then presented as:

V-F2 = 0.327 + 0.688 V-A2.

5.1.5. Model 5: D2 vs R2 and V-A2

The independent parameters of the first model are R2 and V-A2 and the

predicted parameter is D2.

5.1.5.1. Data base for this model is shown in Figure 5.5.

Figure 5.5 shows the independent and predicted parameters of model 5.

Figure 5.5.   Data base for model 5.

5.1.5.2. SPSS output

Table 5.9 and 5.10 shows the ANOVA and coefficient table.

Table 5.9. ANOVA table for model 5

Model	Sum of Squares	df	Mean Square	F	Sig.

Regression	.545	2	.273	13.092	.000
Residual	2.437	117	.021		
Total	2.983	119			

Table 5.10. Coefficient table for model 5

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	S.E. a	Beta		
Const.	.327	.038		8.630	.000
R2	5.596E-03	.005	.105	1.175	.242
V-A2	-.312	.062	-.453	-5.073	.000

5.1.5.3. Numerical model

R2's influence is not significant, so the model for D2 is then presented as: D2 = 0.327 - 0.312 V-A2.

5.1.6.   Model 6: ABS-D2 vs R2 and V-A2

The independent parameters of the first model are R2 and V-A2 and the predicted parameter is ABS-D2.

5.1.6.1. Data base for this model is shown in Figure 5.6.

Figure 5.6 shows the independent and predicted parameters of model 6.
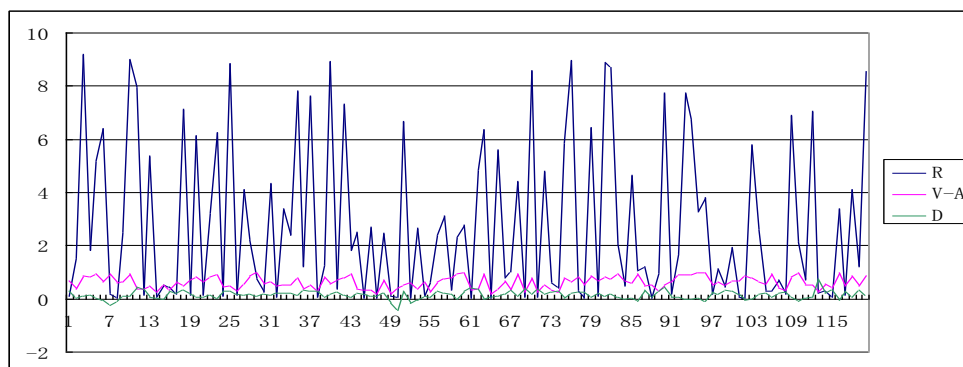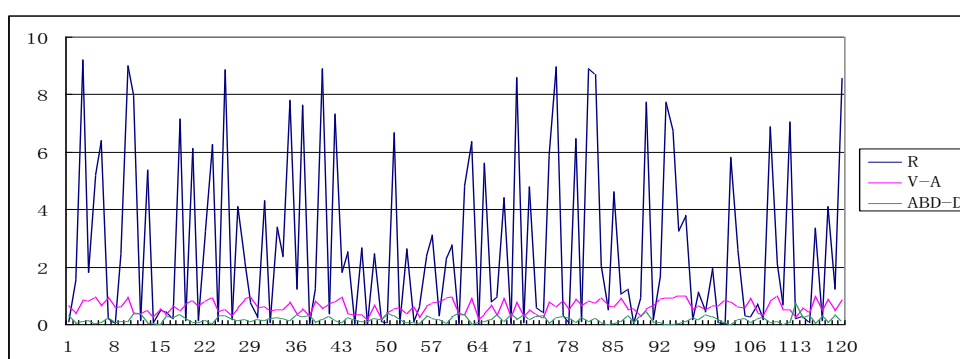

Figure 5.6.   Data base for model 6.

5.1.6.2. SPSS output

Table 5.11 and 5.12 shows the ANOVA and coefficient table.

Table 5.11. ANOVA table for model 6

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	.469	2	.234	19.092	.000
Residual	1.436	117	.012		
Total	1.905	119			

a.   R-Square = 0.246

Table 5.12. Coefficient table for model 6

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	S.E. a	Beta		
Const.	.345	.029		11.88	.000
R2	-1.045E-03	.004	-.025	-.286	.775
V-A2	-.268	.047	-.487	-5.67	.000

5.1.6.3. Numerical model

R2 hardly affects ABS-D2, so the model for ABS-D2 is then presented as:

ABS-D2 = 0.345 - 0.268 V-A2.

5.1.7. Results

Results show that the range of fuzzy values for fuzzy AHP approach has no

significant affect in all models, so it is not an important factor to the difference of the

two approaches. Thus, it is omitted from the model.

On the other hand, the pairwise weight value of AHP is an important factor to all

six models. In conclusion, in the following research there is only one input variable

V-A.

5.2. CVISN project scenario

Previous study in Chapter 4 has worked out the final weight vector W_A for

classical AHP approach and non-fuzzy weight vector W_F for fuzzy AHP approach,

which are listed below.

$$
W_A = \begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ w_4 \\ w_5 \\ w_6 \end{bmatrix} = \begin{bmatrix} 0.121 \\ 0.125 \\ 0.103 \\ 0.297 \\ 0.291 \\ 0.063 \end{bmatrix} \qquad W_F = \begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ w_4 \\ w_5 \\ w_6 \end{bmatrix} = \begin{bmatrix} 0.165 \\ 0.167 \\ 0.147 \\ 0.191 \\ 0.189 \\ 0.142 \end{bmatrix}
$$

Then by previous definition of input and output variables, the input and output

variables for CVISN project are collect and calculate in Table 5.13.

Table 5.13. Input and output variables of CVISN project scenario

Subgroup 1						Subgroup 2					
Pairwise	Input Variable		Output Variable			Pairwise	Input Variable		Output Variable		
Comparison	R	V-A	V-F	D	ABS-D	Comparison	R	V-A	V-F	D	ABS-D
A/C	2.056	1.178	1.122	-0.056	0.056	A/B	1.333	0.973	0.986	0.013	0.013
A/F	11.167	1.911	1.160	-0.751	0.751	A/D	0.974	0.409	0.863	0.455	0.455
B/C	2.500	1.211	1.138	-0.073	0.073	A/E	2.433	0.417	0.870	0.453	0.453
B/F	11.000	1.965	1.177	-0.787	0.787	B/D	0.964	0.420	0.876	0.456	0.456
C/F	5.667	1.622	1.034	-0.588	0.588	B/E	2.558	0.428	0.883	0.454	0.454
D/E	1.946	1.019	1.008	-0.012	0.012	C/D	0.868	0.347	0.770	0.423	0.423
D/F	10.000	4.674	1.344	-3.330	3.330	C/E	1.171	0.354	0.776	0.422	0.422
E/F	10.619	4.585	1.333	-3.251	3.251	C/A	1.609	0.849	0.891	0.043	0.043
B/A	2.400	1.028	1.015	-0.014	0.014	F/A	2.913	0.523	0.862	0.339	0.339
D/A	11.717	2.446	1.158	-1.288	1.288	C/B	1.667	0.826	0.879	0.053	0.053
E/A	14.600	2.399	1.149	-1.250	1.250	F/B	1.913	0.509	0.849	0.340	0.340
D/B	11.377	2.379	1.142	-1.238	1.238	F/C	2.833	0.616	0.967	0.350	0.350
E/B	14.619	2.334	1.133	-1.201	1.201	E/D	1.093	0.981	0.992	0.011	0.011
D/C	11.611	2.882	1.299	-1.582	1.582	F/D	0.909	0.214	0.744	0.530	0.530
E/D	11.867	2.827	1.289	-1.537	1.537	F/E	2.534	0.218	0.750	0.532	0.532

These variables will be divided into six models consistent with the ones in

random rata part and will be evaluated in the next section.

5.3. Predicted interval senario

In this section, basic variables for six statistical models are calculated by pre-introduced methods firstly. Then for each model, prediction intervals of every output variable are calculated for CVISN project. Finally, all output variables are verified based on the prediction intervals.

5.3.1. Basic variables for statistical models

Basic variables for statistical models that are required to calculate prediction intervals in the future include: mean of all input data from the population data ($\bar{x}$), sum of mean square of input variable (S_{xx}), mean square error (MSE) of population data, and the critical value of t test ($t_{0.05/2, n-2}$).

Since only one input variable is significant, the mean of input data, sum of mean square of input variable and the MSE indicate the mean, sum of mean square and the MSE of V-A. What is more, every three models come from one subgroup which consists of 120 data, so the degree of freedom for t distribution is 120-2=118 stays the same for all six models.

The confidence level is α = 0.05, which is the most common level for judgment in practice.

These variables for the six models are calculated and given in Table 5.14.

Table 5.14. Basic output variables for six models

Model	Output Variables			
	$\bar{x}$	S_{xx}	MSE	$t_{0.05/2,120-2}$
V-F1 vs V-A1	1.9482	118.2269	0.180	1.98
D1 vs V-A1	1.9482	118.2269	0.180	1.98
ABS-D1 vs V-A1	1.9482	118.2269	0.140	1.98
V-F2 vs V-A2	0.6168	6.2846	0.021	1.98
D2 vs V-A2	0.6168	6.2846	0.021	1.98

ABS-D2 vs V-A2	0.6168	6.2846	0.012	1.98

5.3.2. Prediction intervals for output variables

Based on Table 5.1, prediction intervals for every output variable are calculated for each model. Prediction intervals are represented by two characteristic values: lower prediction limit (LPL) and upper prediction limit (UPL). To obtain these two values, predicted values ($\hat{y}$) and square of the difference between the specific input value and $\bar{x}$ ($(x_i - \bar{x})^2$) should be calculated first.

Prediction intervals for six models are shown in Table 5.15~5.20.

5.3.2.1 Model 1: V-F1 vs V-A1

Table 5.15 shows the prediction intervals of each predicted parameter, that is V-F1 based on the SPSS outcome of Model 1 in the random data scenario.

Table 5.15. Prediction interval for model 1

Pairwise Comparison	Predicted Value $\hat{y}$	$(x_i - \bar{x})^2$	Prediction Interval	
			LPL	UPL
A/C	1.1252	0.5932	0.2796	1.9709
A/F	1.3978	0.0014	0.5543	2.2414
B/C	1.1376	0.5432	0.2921	1.9830
B/F	1.4178	0.0003	0.5743	2.2614
C/F	1.2904	0.1064	0.4465	2.1343
D/E	1.0663	0.8625	0.2197	1.9128
D/F	2.4258	7.4315	1.5564	3.2953
E/F	2.3926	6.9520	1.5248	3.2604
B/A	1.0695	0.8465	0.2229	1.9160
D/A	1.5970	0.2480	0.7526	2.4414
E/A	1.5796	0.2036	0.7353	2.4238
D/B	1.5721	0.1858	0.7279	2.4163
E/B	1.5551	0.1486	0.7111	2.3992
D/C	1.7590	0.8714	0.9124	2.6056
E/D	1.7385	0.7715	0.8922	2.5847

5.3.2.2 Model 2: D1 vs V-A1

Table 5.16 shows the prediction intervals of each predicted parameter, that is D1 based on the SPSS outcome of Model 2 in the random data scenario. LPL and UPL represent the lower and upper bonds of prediction limits.

Table 5.16. Prediction interval for model 2

Pairwise Comparison	Predicted Value $\hat{y}$	$(x_i - \overline{x})^2$	Prediction Interval	
			LPL	UPL
A/C	-0.0528	0.5932	-0.8984	0.7928
A/F	-0.5130	0.0014	-1.3565	0.3305
B/C	-0.0736	0.5432	-0.9191	0.7718
B/F	-0.5468	0.0003	-1.3903	0.2968
C/F	-0.3317	0.1064	-1.1756	0.5123
D/E	0.0468	0.8625	-0.7998	0.8933
D/F	-2.2484	7.4315	-3.1179	-1.3790
E/F	-2.1923	6.9520	-3.0601	-1.3245
B/A	0.0413	0.8465	-0.8052	0.8878
D/A	-0.8492	0.2480	-1.6936	-0.0048
E/A	-0.8198	0.2036	-1.6641	0.0244
D/B	-0.8072	0.1858	-1.6513	0.0370
E/B	-0.7786	0.1486	-1.6226	0.0655
D/C	-1.1227	0.8714	-1.9693	-0.2761
E/D	-1.0881	0.7715	-1.9343	-0.2418

5.3.2.3 Model 3: ABS-D1 vs V-A1

Table 5.17 shows the prediction intervals of each predicted parameter, that is ABS-D1 based on the SPSS outcome of Model 3 in the random data scenario.

Table 5.17. Prediction interval for model 3

Pairwise Comparison	Predicted Value $\hat{y}$	$(x_i - \overline{x})^2$	Prediction Interval	
			LPL	UPL
A/C	0.1347	0.5932	-0.6111	0.9803
A/F	0.5861	0.0014	-0.1579	1.4296
B/C	0.1551	0.5432	-0.5905	1.0005
B/F	0.6192	0.0003	-0.1247	1.4627
C/F	0.4082	0.1064	-0.3361	1.2521
D/E	0.0370	0.8625	-0.7096	0.8836
D/F	2.2884	7.4315	1.5216	3.1578
E/F	2.2333	6.9520	1.4680	3.1011

B/A	0.0423	0.8465	-0.7042	0.8889
D/A	0.9159	0.2480	0.1712	1.7603
E/A	0.8870	0.2036	0.1425	1.7313
D/B	0.8746	0.1858	0.1301	1.7188
E/B	0.8466	0.1486	0.1022	1.6906
D/C	1.1841	0.8714	0.4375	2.0307
E/D	1.1502	0.7715	0.4038	1.9964

5.3.2.4 Model 4: V-F2 vs V-A2

Table 5.18 shows the prediction intervals of each predicted parameter, that is

V-F2 based on the SPSS outcome of Model 4 in the random data scenario.

Table 5.18. Prediction interval for model 4

Pairwise Comparison	Predicted Value $\hat{y}$	$(x_i\text{-}\overline{x})^2$	Prediction Interval	
			LPL	UPL
A/B	0.9962	0.9518	0.7052	1.2871
A/D	0.6083	2.3698	0.3191	0.8974
A/E	0.6137	2.3453	0.3247	0.9028
B/D	0.6162	2.3345	0.3272	0.9052
B/E	0.6218	2.3095	0.3329	0.9107
C/D	0.5657	2.5638	0.2760	0.8555
C/E	0.5704	2.5422	0.2807	0.8601
C/A	0.9110	1.2085	0.6217	1.2004
F/A	0.6871	2.0302	0.3987	0.9754
C/B	0.8950	1.2601	0.6059	1.1842
F/B	0.6772	2.0713	0.3888	0.9656
F/C	0.7512	1.7734	0.4630	1.0393
E/D	1.0018	0.9357	0.7107	1.2930
F/D	0.4742	3.0077	0.1824	0.7660
F/E	0.4771	2.9932	0.1853	0.7688

5.3.2.5 Model 5: D2 vs V-A2

Table 5.19 shows the prediction intervals of each predicted parameter, that is D2

based on the SPSS outcome of Model 5 in the random data scenario.

Table 5.19. Prediction interval for model 5

Pairwise Comparison	Predicted Value $\hat{y}$	$(x_i\text{-}\overline{x})^2$	Prediction Interval	
			LPL	UPL
A/B	0.0235	0.9518	-0.2674	0.3145

A/D	0.1995	2.3698	-0.0896	0.4886
A/E	0.1970	2.3453	-0.0921	0.4860
B/D	0.1959	2.3345	-0.0931	0.4849
B/E	0.1933	2.3095	-0.0956	0.4822
C/D	0.2187	2.5638	-0.0710	0.5085
C/E	0.2166	2.5422	-0.0731	0.5063
C/A	0.0621	1.2085	-0.2272	0.3515
F/A	0.1637	2.0302	-0.1246	0.4520
C/B	0.0694	1.2601	-0.2197	0.3585
F/B	0.1682	2.0713	-0.1202	0.4566
F/C	0.1347	1.7734	-0.1535	0.4228
E/D	0.0210	0.9357	-0.2702	0.3121
F/D	0.2603	3.0077	-0.0315	0.5520
F/E	0.2590	2.9932	-0.0328	0.5507

5.3.2.6 Model 6: ABS-D2 vs V-A2

Table 5.20 shows the prediction intervals of each predicted parameter, that is

ABS-D2 based on the SPSS outcome of Model 1 in the random data scenario.

Table 5.20. Prediction interval for model 6

Pairwise Comparison	Predicted Value $\hat{y}$	$(x_i - \bar{x})^2$	Prediction Interval	
			LPL	UPL
A/B	0.0843	0.9518	-0.1356	0.3043
A/D	0.2354	2.3698	0.0169	0.4540
A/E	0.2333	2.3453	0.0148	0.4518
B/D	0.2324	2.3345	0.0139	0.4508
B/E	0.2302	2.3095	0.0118	0.4486
C/D	0.2520	2.5638	0.0330	0.4710
C/E	0.2502	2.5422	0.0312	0.4692
C/A	0.1175	1.2085	-0.1012	0.3362
F/A	0.2047	2.0302	-0.0132	0.4227
C/B	0.1237	1.2601	-0.0948	0.3423
F/B	0.2086	2.0713	-0.0094	0.4266
F/C	0.1798	1.7734	-0.0380	0.3976
E/D	0.0821	0.9357	-0.1379	0.3022
F/D	0.2877	3.0077	0.0671	0.5082
F/E	0.2865	2.9932	0.0660	0.5071

5.3.3. Verification of output variables

In this section, output variables of CVISN project are verified according to their

corresponding models. To perform the verification, output values and prediction

intervals are needed. If the output value is within its prediction interval, it is said to be

qualified and is evaluated as 1; otherwise, it is said to be unqualified and is evaluated

as 0.

Verification results for six models are shown in table 5.21~5.26, respectively.

Table 5.21. Verification for model 1

Pairwise Comparison	V-F1	Prediction Interval		Verification Value
		LPL	UPL	
A/C	1.1217	0.2796	1.9709	1
A/F	1.1603	0.5543	2.2414	1
B/C	1.1381	0.2921	1.9830	1
B/F	1.1773	0.5743	2.2614	1
C/F	1.0344	0.4465	2.1343	1
D/E	1.0078	0.2197	1.9128	1
D/F	1.3439	1.5564	3.2953	0
E/F	1.3334	1.5248	3.2604	0
B/A	1.0146	0.2229	1.9160	1
D/A	1.1582	0.7526	2.4414	1
E/A	1.1492	0.7353	2.4238	1
D/B	1.1416	0.7279	2.4163	1
E/B	1.1327	0.7111	2.3992	1
D/C	1.2992	0.9124	2.6056	1
E/D	1.2891	0.8922	2.5847	1

Table 5.22. Verification for model 1

Pairwise Comparison	D1	Prediction Interval		Verification Value
		LPL	UPL	
A/C	-0.0563	-0.8984	0.7928	1
A/F	-0.7505	-1.3565	0.3305	1
B/C	-0.0730	-0.9191	0.7718	1
B/F	-0.7874	-1.3903	0.2968	1
C/F	-0.5877	-1.1756	0.5123	1
D/E	-0.0117	-0.7998	0.8933	1
D/F	-3.3304	-3.1179	-1.3790	0
E/F	-3.2514	-3.0601	-1.3245	0
B/A	-0.0135	-0.8052	0.8878	1
D/A	-1.2880	-1.6936	-0.0048	1

E/A	-1.2502	-1.6641	0.0244	1
D/B	-1.2377	-1.6513	0.0370	1
E/B	-1.2011	-1.6226	0.0655	1
D/C	-1.5824	-1.9693	-0.2761	1
E/D	-1.5374	-1.9343	-0.2418	1

Table 5.23. Verification for model 1

Pairwise Comparison	ABS-D1	Prediction Interval		Verification Value
		LPL	UPL	
A/C	0.0563	-0.6111	0.9803	1
A/F	0.7505	-0.1579	1.4296	1
B/C	0.0730	-0.5905	1.0005	1
B/F	0.7874	-0.1247	1.4627	1
C/F	0.5877	-0.3361	1.2521	1
D/E	0.0117	-0.7096	0.8836	1
D/F	3.3304	1.5216	3.1578	0
E/F	3.2514	1.4680	3.1011	0
B/A	0.0135	-0.7042	0.8889	1
D/A	1.2880	0.1712	1.7603	1
E/A	1.2502	0.1425	1.7313	1
D/B	1.2377	0.1301	1.7188	1
E/B	1.2011	0.1022	1.6906	1
D/C	1.5824	0.4375	2.0307	1
E/D	1.5374	0.4038	1.9964	1

Table 5.24. Verification for model 1

Pairwise Comparison	V-F2	Prediction Interval		Verification Value
		LPL	UPL	
A/B	0.9856	0.7052	1.2871	1
A/D	0.8634	0.3191	0.8974	1
A/E	0.8701	0.3247	0.9028	1
B/D	0.8760	0.3272	0.9052	1
B/E	0.8829	0.3329	0.9107	1
C/D	0.7697	0.2760	0.8555	1
C/E	0.7757	0.2807	0.8601	1
C/A	0.8915	0.6217	1.2004	1
F/A	0.8619	0.3987	0.9754	1
C/B	0.8786	0.6059	1.1842	1
F/B	0.8494	0.3888	0.9656	1
F/C	0.9668	0.4630	1.0393	1
E/D	0.9922	0.7107	1.2930	1
F/D	0.7441	0.1824	0.7660	1
F/E	0.7499	0.1853	0.7688	1

Table 5.25. Verification for model 5

Pairwise Comparison	D2	Prediction Interval		Verification Value
		LPL	UPL	
A/B	0.0130	-0.2674	0.3145	1
A/D	0.4546	-0.0896	0.4886	1
A/E	0.4534	-0.0921	0.4860	1
B/D	0.4557	-0.0931	0.4849	1
B/E	0.4544	-0.0956	0.4822	1
C/D	0.4227	-0.0710	0.5085	1
C/E	0.4219	-0.0731	0.5063	1
C/A	0.0426	-0.2272	0.3515	1
F/A	0.3385	-0.1246	0.4520	1
C/B	0.0530	-0.2197	0.3585	1
F/B	0.3404	-0.1202	0.4566	1
F/C	0.3503	-0.1535	0.4228	1
E/D	0.0113	-0.2702	0.3121	1
F/D	0.5302	-0.0315	0.5520	1
F/E	0.5318	-0.0328	0.5507	1

Table 5.26. Verification for model 6

Pairwise Comparison	ABS-D2	Prediction Interval		Verification Value
		LPL	UPL	
A/B	0.0130	-0.1356	0.3043	1
A/D	0.4546	0.0169	0.4540	0
A/E	0.4534	0.0148	0.4518	0
B/D	0.4557	0.0139	0.4508	0
B/E	0.4544	0.0118	0.4486	0
C/D	0.4227	0.0330	0.4710	1
C/E	0.4219	0.0312	0.4692	1
C/A	0.0426	-0.1012	0.3362	1
F/A	0.3385	-0.0132	0.4227	1
C/B	0.0530	-0.0948	0.3423	1
F/B	0.3404	-0.0094	0.4266	1
F/C	0.3503	-0.0380	0.3976	1
E/D	0.0113	-0.1379	0.3022	1
F/D	0.5302	0.0671	0.5082	0
F/E	0.5318	0.0660	0.5071	0

CHAPTER 6. DISCUSSION

6.1. Comparison of AHP and fuzzy AHP approaches

In the first scenario of this research, a comparison of classic AHP and fuzzy AHP approaches were performed to give a numerical illustration on how some factors affect the difference given by the two approaches. In this way, it adds useful knowledge to the relationship between two existing problems: (1) What factors bring the difference between classic AHP and Fuzzy AHP? (2) How different the results are given by the two approaches?

According to the hypothesis given by Chapter 3, result in this part concludes that in general situation, the pairwise weight values of AHP approach is a significant factor to the differences while the range of fuzzy values for Fuzzy AHP approach is not. Furthermore, the fuzzy AHP narrows the span of the criteria weights, excluding two extreme circumstances in which fuzzy AHP may increase the comparative weights of specific criterion.

To be specify, the first subgroup of model illustrates that, for fuzzy AHP, the pairwise weight values increase when the pairwise weight values of AHP increase; but the incremental rate is smaller, which means that the larger the pairwise weight values, the larger the differences between the two approaches are. The second subgroup of models illustrates that, for fuzzy AHP, the pairwise weight values decrease when the pairwise weight values of AHP decrease; but the decremental rate is smaller, which means that the smaller the pairwise weight values, the larger the differences between the two approaches are.

In conclusion, fuzzy AHP approach produces the weight for each pair of criteria with the same tendency as classic AHP approach, but it narrows them. This outcome is attributed to the uncertainty of evaluators' preferences on the criteria. The uncertainty results in the span of fuzzy pairwise comparison numbers which balances the weights of each criterion.

There are two extreme situations, under which the conclusion by previous modeling does not hold true.

(1) Weight value equals to 0

There is one extreme circumstance that if one criterion whose weight is weaker than all of the others, fuzzy AHP will have the weight of this criterion equals to 0. For example, for criterion i, $a_{ij} < 1$ for all j, then $W_i = 0$. In this situation, fuzzy AHP enlarges the comparative weight of this criterion.

(2) Weight value equals to 1

There is another extreme circumstance that if one criterion whose weight is stronger than all of the others, fuzzy AHP will have the weight of this criterion equals to 1. For example, for criterion i, $a_{ij} < 1$ for all j, then $W_i = 1$. In this situation, fuzzy AHP also magnifies the comparative weight of this criterion.

6.2. Criteria ranking for CVISN project

The verification based on prediction intervals suggested that fuzzy AHP is an appropriate approach to deal with the multiple criteria decision making problem for CVISN project. This conclusion is on the basis of the assumption that the pairwise

comparison values gained from stakeholders, who have the equal influence on the scores of criteria, are considered to be a series of possible pairwise comparison values obtained by a fictitious decision maker. Only in this way can this problem be solved in a fuzzy AHP circumstance.

The detailed information for fuzzy AHP being appropriate in this specified problem is stated below:

(1) For each of the first subgroup of models which have the pairwise comparison value larger than 1, 13 out of 15 predicted variables are within prediction intervals.

(2) The only two predicted variables that are out of prediction intervals are the pairwise comparison value between D and F, and E and F. By careful observation of these three criteria, it is easy to find out from the final weight vector gained by classical AHP that criteria D and E are the most important criteria with the highest scores (0.297 and 0.291 respectively) while criterion F is the weakest criteria with the lowest score (0.063). As well, fuzzy AHP approach provided the same trend results that criteria D and E get the highest scores (0.191 and 0.189 respectively) and criterion F gets the lowest score (0.142), even though these results are greatly narrowed.

(3) This fact makes the existence of these two outliers make sense. Firstly, fuzzy AHP narrows the weights among criteria; secondly, the more extreme the weights given by classical AHP are, the greater the fuzzy AHP narrows them; thirdly, these two pairs of criteria are all the combinations of the most

important criterion and the least important criterion, which means that they are all combinations of criterion with extreme weight. As a result, the differences between fuzzy AHP and classical AHP on these two pairs of criteria are large enough to go beyond the predicted intervals.

(4) For the first two of the second subgroup of models which have the pairwise comparison value smaller than 1, all 15 predicted variables are within the prediction intervals. These two models indicate that this problem is well satisfied by fuzzy AHP.

(5) For the last model, there are 6 predicted variables out of 15 failed to be within the prediction intervals.

(6) It is obviously that these 6 variables do not exceed the prediction intervals a lot. Hence, it is hard to confirm the conclusion that according to this model, fuzzy AHP is not suitable.

6.3. Overall conclusions

First, this research works on the comparison of classical AHP and fuzzy AHP with 240 randomly generated data. By building a series of statistic models, this research concludes that criteria weights given by fuzzy AHP follow the same tendency as the ones given by classic AHP approach; they concentrate to a smooth vector of weights. This conclusion is not acceptable for two extreme situations. These models are benchmarks for the application of these two approaches into CVISN project.

Second, this research uses both classical AHP and fuzzy AHP approaches to deal with the multiple criteria decision making problem of CVISN project. Two weight vectors show the same trends, which are coincident with the outcomes from the random data.

Third, according to the benchmark, this research verifies the results of the CVISN project using prediction interval. Except two pairs of extreme criteria, other predicted variables are all within the prediction interval. Moreover, these two outliers are understandable and acceptable. Hence, fuzzy AHP is appropriate for CVISN project.

In conclusion, fuzzy AHP is a suitable approach for the CVISN project based on some assumptions. Again, it takes care of more stakeholders' preferences compared with classical AHP. As a result, this research takes the weight vector of the criteria given by fuzzy AHP approach to provide support for further research.

The final weight ranking of the six technical requirements is:

$$W_F = \begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ w_4 \\ w_5 \\ w_6 \end{bmatrix} = \begin{bmatrix} 0.165 \\ 0.167 \\ 0.147 \\ 0.191 \\ 0.189 \\ 0.142 \end{bmatrix}$$

6.4. Limitations

There are three limitations for this research.

(1) The number of criterion was arbitrarily chosen as 4. This limitation came from the assumption.

(2) Consistency Ration (CR) was not taken into account to judge the consistency

of the system.

(3) Confidence level α is chosen as 0.05, which is most common used. But under

this confidence level, the outputs are not very well. Once we changed the for

a little bit, from 0.05 to 0.02, then the critical value of t test ($t_{0.02/2,n-2}$) will be

changed to 2.33 and the prediction interval for the last model will be changed

in Table 6.1.

Table 6.1. VERIFICATION FOR MODEL 6 WITH DIFFERENT CONFIDENCE LEVEL

Pairwise Comparison	ABS-D2	Prediction Interval		Verification Value
		LPL	UPL	
A/C	0.0130	-0.1745	0.3432	1
A/F	0.4546	-0.0217	0.4926	1
B/C	0.4534	-0.0238	0.4904	1
B/F	0.4557	-0.0247	0.4894	1
C/F	0.4544	-0.0269	0.4872	1
D/E	0.4227	-0.0058	0.5098	1
D/F	0.4219	-0.0075	0.5079	1
E/F	0.0426	-0.1399	0.3749	1
B/A	0.3385	-0.0517	0.4612	1
D/A	0.0530	-0.1335	0.3809	1
E/A	0.3404	-0.0479	0.4651	1
D/B	0.3503	-0.0765	0.4361	1
E/B	0.0113	-0.1768	0.3411	1
D/C	0.5302	0.0281	0.5472	1
E/D	0.5318	0.0271	0.5460	1

In the future, the number of criterion can be considered as another factor that

may affect the differences between classical AHP and fuzzy AHP approaches. What is

more, system consistency can be another aspect to extend this research. Also, the

confidence level will be considered with more values to specify the results of the

CVISN project.

CHAPTER 7. CONTRIBUTION TO THE BODY OF KNOWLEDGE

Decision making problem is one of most common problem in Operations Research field. AHP approach is an effective and popular way to deal with this problem. As a result, it is well known in Operations Research field as a decision structuring tool. In 2008, the major international society for operations research formally recognized AHP's broad impact on its field.

This paper works on the differences between classical AHP and fuzzy AHP approaches, with the purpose of finding out how the factors influence the differences between the two approaches. In this way, this paper contributes to the development of Operations Research.

In addition, based on the comparison, this paper provides the CVISN project with reasonable and comprehensive criteria ranking of six important technical requirements. As a result, this paper has practical contribution.

The two AHP approaches used in this paper have been maturely developed and well applied into many fields. Also their operations are proved to be simple. One is classical AHP approach, with the geometric mean as the average of different pairwise comparison values. The other one is Chang's extent Fuzzy AHP approach.

Literature research has found that there are many studies on the differences between classical AHP and fuzzy AHP. These studies can be divided into two aspects. One is about the theoretical methods, which is focusing on how the differences come out; the other one is about the final results, which is emphasizing the differences between two weight vectors given by corresponding approaches. The connection

between these two aspects is a gap in previous studies.

The detailed contributions to the Operation Research of this paper are listed below.

In the first place, this paper proposes two potential impacts which affect the differences between classical AHP and fuzzy AHP approaches. They are the pairwise comparison of one criterion over another given by classical AHP and the range of the fuzzy number for pairwise comparison given by fuzzy AHP.

In the second place, this paper generates useful information for the relationship between the two aspects of previous researches. This paper explores how the factors that give rise to the differences affect the weight vectors given by these two AHP approaches. In other words, this paper works out the relationships between the two proposed impacts and the differences coming from classical AHP and fuzzy AHP. Results show that the range of fuzzy values of fuzzy AHP approach is not an important factor to the differences of the two approaches while the pairwise comparison values of classical AHP significantly affect the differences. Moreover, fuzzy AHP approach produces the weight for each pair of criteria with the same tendency as classic AHP approach, but it narrows them.

In the third place, data used in the comparison are randomly generated data. 240 random data are more enough to perform statistic modeling. Simple linear regression models are built to generate the relationships between the differences given by the two approaches and the potential impacts. Hence, this paper compares the differences between classical AHP and fuzzy AHP approaches in a statistical way and the

differences are in the form of statistical linear regression models.

In the forth place, this paper is a case study of the comparison of classical AHP and fuzzy AHP approaches. Data coming from CVISN project are used to be an example to conduct the comparison.

In the fifth place, prediction intervals are used to verify the results given by the CVISN project. Prediction interval is a common method for validation of any single predicted value in statistics. 240 random data are data population to create the benchmark for prediction intervals by building the statistical regression models.

In the sixth place, this paper meets the research objective and provides the CVISN project with a comprehensive ranking of the six technical requirements. This ranking will be used in future research of CVISN project for the purpose of RFID system selection.

CHAPTER 8. REFERENCES

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