TR
SIIRT UNIVERSITY
INSTITUTE OF SCIENCE

FUZZY EXPERT SYSTEMS, APPLICATIONS IN LIVESTOCK AND A SAMPLE DESIGN

MS THESIS

Aras Ayoob AMEEN
(153109003)

Department of Animal Science

Supervisior: Asst. Prof. Dr. Nazire MİKAİL

NOVEMBER - 2017
SİİRT

THESIS ACCEPTANCE AND CONFIRMATION

The thesis study entitled " Fuzzy expert systems, applications in livestock and a sample design" prepared by Aras Ayoob Ameen has been accepted as a Master Degree thesis with majority of votes by the following jury on the date of 10/11/2017 at Siirt University, Institute of Sciences, Department of Animal Science.

Jury members	**Signature**
Chairman Asst. Prof. Dr. Humar KAHRAMANLI	…………………
Supervisior Asst. Prof. Dr. Nazire MİKAİL	…………………
Member Asst. Prof. Dr. Muhammet Ali KARA	…………………..

I confirm the above conclusion

Assoc. Prof. Dr. Koray ÖZRENK
Director of Institute of Science

This thesis study was supported with the Project No 2016-SİÜFEB-21 by Siirt University.

DECLARATION PAGE

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Aras Ayoob AMEEN

Note: In this thesis, the use of original and other source notifications, tables, figures and photographs without reference, it is subject to provision of law No 5846 on Intellectual and Artistic Works.

PREFACE

Praise be to God for completion and thank him for the pleasure. The most important thing that God preferred to me was the reasons for completing the research. Like any other research that has not been completed, it is only by extending the help of many who have time to remember and thank them.

Starting and before all, I would like to thank the Asst. Prof. Dr. Nazire MİKAİL. She put the task of supervising this research and gave me her valuable observations and guidance and encouraged me constantly. Her virtuous efforts, her valuable observations and her good encouragement have had the effect of lighting many aspects of the thesis, I can only ask God to reward you with the best reward.

I would like to thank to Asst. Prof. Dr. Humar KAHRAMANLI for providing an opportunity to use MATLAB Software Fuzzy Logic Toolbox in Selçuk University for modeling the data.

And thanks to Mr. Beshir ÇEVİK, and thanks to my dear friends Serdar ALTUNTAŞ, Khebat, and Ako for their great help. And I thank my family who helped me a lot.

I dedicate this thesis to my mother and my father, and to my brother, and sister**.** To all my friends. To who has helped me and taught me so far.

Aras Ayoob AMEEN
SİİRT-2017

TABLE OF CONTENTS

Page

PREFACE iv

TABLE OF CONTENTS v

LIST OF TABLES vii

LIST OF FIGURES viii

LIST OF PICTURES ix

LIST OF ABBREVIATIONS AND SYMBOLS x

ÖZET xi

ABSTRACT xii

1. INTRODUCTION 1

2. LITERATURE REVIEW 3

2.1. Fuzzy Expert System Applications in Livestock 3
2.2. Conventional Methods in Live Body Weight Prediction 5

3. MATERIAL AND METHODS 11

3.1. Material 11
3.1.1. Hair goats 11
3.1.2. The climatic and geographic structure of Siirt 12
3.1.3. The animals used in the research 13
3.2. Method 15
3.2.1. Fuzzy logic 15
3.2.2. Fuzzy sets 18
3.2.3. Linguistic variables and hedges 23
3.2.4. Operations of fuzzy sets 27
3.2.5. Fuzzy rules 33
3.2.6. Fuzzy inference 36
3.2.7. Building a fuzzy expert system 44
3.2.8. Performance criteria 56

4. RESULTS AND DISCUSSIONS 59

4.1. FES Design For Live Body Weight Prediction 59
4.2. Fuzzification 61
4.3. Fuzzy rules 63
4.4. Inference method 64
4.5. Defuzzification 64

5. CONCLUSION AND RECOMMENDATIONS 69

5.1. Conclusions 69
5.2. Recommendations 69

6. REFERENCES 71

CURRICULUM VITAE 75

LIST OF TABLES

Page

Table 3.1. Existence of goats in continents 11
Table 3.2. Existence of goats in Turkey during 1991-2016 11
Table 3.3. Degree of membership of ‘tall men’. 19
Table 3.4. Representation of hedges in Fuzzy Logic. 26
Table 3.5. Linguistic variables and their ranges 46
Table 3.6. The rule table 49
Table 4.1. Descriptive statistics of the obtained data 59
Table 4.2. Correlation coefficients between body measurements and live body weight 59
Table 4.3. Linguistic terms used for the body measurements 61
Table 4.4. Rule sets for the FES 63

LIST OF FIGURES

Page

Figure 3.1. Range of logical values in Boolean and Fuzzy logic: (a) Boolean logic; (b) Fuzzy logic 17
Figure 3.2. Crisp (a) and fuzzy (b) sets of 'tall men' 20
Figure 3.3. Crisp (a) and fuzzy (b) sets of short, average and tall men 22
Figure 3.4. Representation of crisp and fuzzy subset of X 22
Figure 3.5. Fuzzy sets with *very* hedge 25
Figure 3.6. Operations on classical sets 27
Figure 3.7. Operations of fuzzy sets 30
Figure 3.8. Fuzzy sets of *tall* and *heavy* men 34
Figure 3.9. Monotonic selection of values for man weight 34
Figure 3.10. The basic structure of Mamdani-style fuzzy inference 38
Figure 3.11. The AND *product* fuzzy operation 40
Figure 3.12. Clipped (a) and scaled (b) membership functions 41
Figure 3.13. The centroid method of defuzzification 42
Figure 3.14. Defuzzifying the solution variable's fuzzy set 42
Figure 3.15. The basic structure of Sugeno-style fuzzy inference 43
Figure 3.16. Fuzzy sets of mean delay m 47
Figure 3.17. Fuzzy sets of number of servers s 47
Figure 3.18. Fuzzy sets of repair utilization factor p 48
Figure 3.19. Fuzzy sets of number of spares n 48
Figure 3.20. The square FAM representation 49
Figure 3.21. Cube FAM and sliced cube FAM representations 50
Figure 3.22. Three-dimensional plots for rule base 1 53
Figure 3.23. Three dimensional plots for rule base 2 54
Figure 3.24. Modified fuzzy sets of number of servers s 54
Figure 3.25. Cube FAM of rule base 3 55
Figure 3.26. Three dimensional plots for rule base 3 55
Figure 4.1. Structure of the developed FES 59
Figure 4.2. Relation between HG and LBW 59
Figure 4.3. Relation between BD and LBW 60
Figure 4.4. Relation between BL and LBW 60
Figure 4.5. 3D representation of LBW by BD and HG 60
Figure 4.6. 3D representation of LBW by BL and HG 61
Figure 4.7. 3D representation of LBW by BD and BL 61
Figure 4.8. Membership function graphic for HG 62
Figure 4.9. Membership function graphic for BD 62
Figure 4.10. Membership function graphic for BL 63
Figure 4.11. Membership function graphic for LBW 63
Figure 4.12. Result of FES 65
Figure 4.13. Case, where two rules are fired at the same time 66
Figure 4.14. Comparison of Actual and FES predicted LBWs 66
Figure 4.15. Correlation between Actual and FES predicted LBWs 67

LIST OF PICTURES

Page

Picture 3.1. Measuring the Heart Girth 14
Picture 3.2. Measuring the Body Depth 14
Picture 3.3. Measuring the Body Length. 15
Picture 3.4. Measuring the Live Body Weight 15

LIST OF ABBREVIATIONS AND SYMBOLS

Abbreviation	**Statement**
FES	**:** Fuzzy Expert System
FL	**:** Fuzzy Logic
ES	**:** Expert System
HG	**:** Heart Girth
BD	**:** Body Depth
BL	**:** Body Length
LBW	**:** Live Body Weight
R^2	**:** Determination Coefficient
RMSE	**:** Root Mean Squared Error
MAPE	**:** Mean Absolute Percentage Error
MPE	**:** Mean Absolute Percentage Error
LW	**:** Live Weight
CD	**:** Chest Depth
TG	**:** Thoracic Girth
HAW	**:** Height at Withers
BDL	**:** Body Length
HW	**:** Hip Width
RH	**:** Rump Height
CB	**:** Cannon Bone Length
NG	**:** Neck Girth
HH	**:** Hip Height
AP	**:** Abdominal Periphery
RH	**:** Rump Height
IA	**:** Image Analysis

Symbol	**Statement**
μ(x)	: membership function
λ	: accuracy ratio

ÖZET

YÜKSEK LİSANS TEZİ

BULANIK UZMAN SİSTEMLER, HAYVANCILIKTA UYGULAMALARI VE ÖRNEK BİR TASARIM

Aras Ayoob Ameen

Siirt Üniversitesi Fen Bilimleri Enstitüsü
Zootekni Anabilim Dalı

Danışman : Yrd. Doç. Dr. Nazire MİKAİL

2017, 74 Sayfa

Bu çalışmada bulanık mantık ve bulanık uzman sistemler genel olarak tanıtılmış, hayvancılıkta geliştirilmiş olan bulanık uzman sistemlere değinilmiş ve bir uzman sistemin tasarlanması amaçlanmıştır.

Materyal olarak Siirt ilinde özel işletmede yetiştirilen 81 kıl keçisinin göğüs çevresi, vücut derinliği ve vücut uzunluğu verileri toplanmıştır. Bu veriler kullanılarak canlı ağırlık tahmini için bulanık uzman sistem tasarlanmıştır. Uygulamada Matlab Paket Programı Fuzzy Logic Toolbox kullanılmıştır. Tasarlanan sistem 29 kural ile çalışmaktadır. Çıkarım yöntemi olarak Mamdani çıkarım yöntemi, durulaştırma yöntemi olarak ise Ağırlık merkezi yöntemi seçilmiştir.

Çalışma sonucunda geliştirilmiş sistemde tahmin edilen canlı ağırlıklar ile gerçekte tartılarak elde edilen canlı ağırlık verileri arasında r=0.95 korelasyon ilişkisi bulunmuştur. Modelin belirlilik katsayısı R^2=0.90 olarak hesaplanmıştır.

Sonuç olarak, bulanık uzman sistemlerin belirsizliklerin ve eksik verilerin bulunduğu hayvancılıkta iyi sonuç verdiği gösterilerek, ileride daha çok uygulamanın geliştirilmesi önerilmiştir.

Anahtar Kelimeler: Bulanık mantık, uzman sistem, kıl keçisi, canlı ağırlık tahmini

ABSTRACT

MS THESIS

FUZZY EXPERT SYSTEMS, APPLICATIONS IN LIVESTOCK AND A SAMPLE DESIGN

Aras Ayoob Ameen

The Institute of Science of Siirt University
The Degree of Master of Science
in Animal Science

Supervisior : Asst. Prof. Dr. Nazire MİKAİL

2017, 74 Pages

The aim of this study, to introduce fuzzy logic and fuzzy expert systems, fuzzy expert systems developed in livestock and to design an expert system.

As material, the heart girth, body depth and body length data of 81 hair goats grown in Siirt province were collected. Using this data, a fuzzy expert system was designed for live body weight prediction. Matlab Programme Fuzzy Logic Toolbox was used for development. The designed system works with 29 rules. The Mamdani inference method was used as inference method and the Centroid method was chosen as the defuzzification method.

It was found a correlation $r = 0.95$ between the live body weights predicted by developed system and the live body weights data obtained by actually weighing. The determination coefficient of the model is calculated as $R^2 = 0.90$.

As a result, it was shown that fuzzy expert systems have better results in livestock with uncertainties and incomplete data and development these kinds of systems in the future was reccommended.

Keywords: Fuzzy logic, expert system, hair goat, live body weight prediction

1. INTRODUCTION

Fuzzy Logic (FL) approach was introduced in an article published by Lotfi Zadeh from University of California, Berkley in 1965. Having increased gradually up to now since then, fuzzy logic can be defined as a solid mathematical model set to explain and work with uncertainties. As is known, statistics and probability theories work with certainties rather than uncertainties, however, world of human is laden with vagueness. Therefore, mankind has been required to work with uncertainties to develop the ability of reasoning. The most significant feature of fuzzy sets is its being able to model verbal and digital information and data containing uncertainties concurrently into the human brain in closest way. Behind the best-decision making and modeling process within the automation and atmosphere of uncertainty underlies fuzzy logic proposition and reasoning through smart and expert systems, which are common in today's technology.

First areas of applications of fuzzy logic systems (commercially) were cement industry and water treatment systems. Afterwards, fuzzy logic was drawn upon in various areas including Image Processing, Time Series-Based Estimation, Solving Control Problems, Communications, Engineering, Medicine, Sociology, Psychology, Management:

- ✓ In Biology and Medicine to apply in fuzzy logic based diagnostic systems, to do cancer researches, to process fuzzy logic based prosthesis devices, to analyse fuzzy logic based movement disorders,
- ✓ In Management and Decision Supports to apply in fuzzy logic based site selection, to make fuzzy logic-assisted military decisions (frightening sounds), to determine fuzzy logic based market sales strategies,
- ✓ In areas of Economy and Finance to apply in fuzzy-modelling of complex sales systems and fuzzy logic based trade systems, to analyse fuzzy logic based cost-benefits, to assess fuzzy logic based investments,
- ✓ In Environmental Sciences to apply in fuzzy logic based weather forecast, to conduct fuzzy logic based water quality control,
- ✓ In Engineering and Computer Sciences to apply in fuzzy database systems and fuzzy logic based earthquake forecasts, to conduct control of automation of fuzzy logic based nuclear businesses, to design fuzzy logic based computer networks, to assess

fuzzy logic based architectural designs, to apply in fuzzy logic based control systems,

- ✓ In Research Studies to apply in fuzzy logic based planning and modelling and fuzzy logic based source decomposition,
- ✓ In Identification and Classification of Mould to identify fuzzy logic based speeches and fuzzy logic based hand-writings, fuzzy logic based facial characters, to analyse fuzzy logic based military orders and to research fuzzy picture,
- ✓ In Psychology to analyse fuzzy logic based human behaviours, to study fuzzy logic based perpetration and prevention of it,
- ✓ In Reliability and Quality Control to apply in fuzzy logic based error prediction, to monitor and control production line.

Today fuzzy logic has taken place widespread not only in designing and manufacturing but also in practice with what we call smart robots as integral parts of our life within the area of technology.

Recently in Turkey fuzzy logic has an important place in learning and application of system and control principles, at least in scientific and research areas. Research and Development units of many international businesses have been needed fuzzy system and control mechanisms. This necessity has emerged in Turkey as well (Şen, 2001).

An expert system (ES) is one of the programming methods that, like-minded people, can decide, so people aiming to solve these problems by modeling (Nabiyev, 2005). The purpose of an expert system is to solve problems that can be solved by a human expert. An expert system can be expressed as a transition from data processing to knowledge processing. In data processing, when the database is processed efficiently depending on an algorithm, in information processing for example heuristic (experience-based) method issues rules and facts which consists of the knowledge base is efficiently processed without being bound by any algorithm (Allahverdi, 2002).

The objective of livestock is to maintain and even to increase profitability. For this purpose, fuzzy expert systems (FES) can help the farmers to achieve their goals.

In current study FES and some applications in livestock were introduced and a sample FES design for live weight prediction in hair goats was developed.

2. LITERATURE REVIEW

2.1. Fuzzy Expert System Applications in Livestock

Fuzzy logic based expert systems recently has begun to be implemented in livestock; some examples of the studies are given below.

Wade et al. (1998), stated that in their study based on monthly production data, if the cows have lower milk yield, longer birth interval and older ages then culling can be done easily but it is difficult to decide when the milk yield and age are high and the birth interval is long. In the fuzzy logic model, yield index, parity and reproductive efficiency evaluated as input and culling as an output. Consequently, they decided which animals will be culled from the herd according to the results.

De Mol and Woldtf (2001) in their study, tried to estimate which cow are in estrus, which cow is infected with mastitis by considering activity, milk temperature and electrical conductivity properties for each cow. They stated that the mastitis is the basic problems of dairy cattle farms and a very costly disease, therefore early diagnosis of the mastitis is very important. Also, they stated that the chance of visual diagnosis of udder infections in automatic milking systems is very low, but in these automatic systems, diseases can be detected based on some data such as milk yield, milk temperature and electrical conductivity.

Firk et al. (2002a) have benefited from fuzzy logic for the correct detection of estrus in the farms having herd management software. For this purpose, they used cow activity (number of steps) and the period lasts from the latest estrus. As a result, they decided that the cow is not in estrus when the following situations: the activity is low; the period from the latest estrus is short, normal, longer than normal and long; activity is medium; the period from the latest estrus is short and longer than normal; activity is high and the period from the latest estrus is short. In the other combinations, they agreed that the cow is in estrus.

In another study, Firk et al. (2002b) stated that the accuracy of fuzzy logic model is enhanced and its error is reduced when the activity, milk yield, milk flow rate and electrical conductivity evaluated all together with adding the period lasts from the latest estrus.

Wang and Samarashinge (2005) tried to envisage a model which can detect mastitis online in the farms using automatic milking system. They stated that it is possible to develop systems which can diagnose also mastitis during milking in automatic milking system thanks to measuring electrical conductivity, milk yield and milk temperature.

Cavero et al., (2006) studied to determine mastitis by a fuzzy expert system based on the data of electrical conductivity, milk production rate and milk flow rate. The researchers evaluated the model according to sensitivity, specificity and error ratio and reported that the specificity of mastitis diagnose changes between 75.8% and 93.9% and the error ratio varied from 41.9% to 95.5% when the sensitivity ratio is at least 80%.

Alizadeh et al. (2008) in their study introduced a novel application of fuzzy logic based expert systems for type judging of dairy cattle.

Luis et al, (2011) in their work developed a system based on fuzzy rules, which indicates the body mass index of ruminant animals in order to obtain the best time to slaughter. The performance validation of the system was based on a statistical analysis using the Pearson correlation coefficient of 0.923, representing a high positive correlation, indicating that the proposed method is appropriate.

Memmedova et al. (2011) have demonstrated a sample model for culling the animals by using a ranking list prepared from first calving age, calving interval and lactation milk yield properties.

In a study carried out by Memmedova and Keskin (2011) in Holstein cows to detect estrus correctly, it was reported that the cows in estrus can be determined with an accuracy of 98% that can be accepted as high ratio by using a fuzzy logic model which evaluates cow activity feature, cow type for this property and the period lasts from the latest estrus together.

Taşdemir et al. (2011), in their study aimed at determining body sizes of Holstein cows through image analysis (IA) and estimating live weights (LW) of them using body sizes along with a fuzzy logic based model, created an image atmosphere in a huge cattle farm, stating that 0number of cows were determined. During the first stage, digital images of each animal was taken by cameras and body sizes, such as wither height (WH), hip height (HH), body length (BL) and hip width (HW), were measured manually and through meter, laser and test strip. LWs of cows were available at a weighing scale and data were recorded automatically in a computer. During the second stage, images were analyzed through IA method and Delphi programming language and body sizes were calculated. Values measured manually were determined to be very close to IA results. As a result, a fuzzy system was developed by using body sizes. This Fuzzy System was developed via MATLAB software. Weights estimated via methods developed were compared with those in Information Based System and platform scale. Correlation coefficient (R^2 = 0.99) was calculated. A statistically significant relation was determined among the compared data.

Neto et al, (2014) in their paper tried to develop a fuzzy inference based on expert system to help preventing lameness in dairy cattle. Hoof length, nutritional parameters and flor material properties (roughness) were used to build the fuzzy inference system.

Mikail and Keskin, (2015) in their study showed that, subclinical mastitis can be diagnosed at an early stage with the help of fuzzy logic-based expert systems which interpret the data like daily milk yield, electrical conductivity, automatic milking duration and season in dairy farms using herd management software.

2.2. Conventional Methods in Live Body Weight Prediction

Pesmen and Yardimci (2008), in their paper investigated the estimation of live weight in Saanen Goats. The data was collected from 70 goats. The average live weight, heart girth, withers height, chest depth, shank circumference and body length parameters were calculated. According to the results of study the highest correlation determined between live weight and heart girth. Within the study in which weight estimation was conducted for Saanen goats, 70 goats were used and separated into two groups. The first group included goats at age range of 2-2.5 during the first lactation period while the second group embodied goats ready for the first insemination. In the study, among the values measured were values of average weight, heart girth, shaft girth, toughness height, body length and chest depth. While average weight value of the first group goats was 55.37 kg, that of second group goats was 41.03 kg. While heart girth value of the first group goats was 91.57 cm on average, that of second group goats was found to be 84.00 cm on average. Considering the measures of shaft girth, it was found that while shaft girth value of the first group goats amounted to 9.32 cm, it was 8.86 cm for that of second group goats. While 66.94 cm was calculated to be average toughness height value for the first group goats, it was determined as 62.07 cm for that of second group goats. Given the body length values of the goats, which are considered as a crucial characteristics of the goats, while the first group goats were measured to have values at 109.75 cm, the second group goats were found to have values of 101.55 cm. The last data obtained in this study was values related to the chest width. Being important especially in relation to accommodation to nutrition conditions, chest width value was found to be 32.55 cm as a high value for the first group goats while the related value was second to the first group with an average value of 30.27 cm. As a result of this study, LW = -151,295 + 1,067 * HG + 3,262 * BL + 0,167 * SC + 0,604 * WH + 0,254 * CD was equated for the first group goats whereas LW = -64,753 + 0,863 * HG + 0,717 * BL - 0,029 * SC + 0,207 * WH + 0,254 * CD was equated for the second group of goats. Moreover, it was concluded that live weight could be estimated through statistical methods using various body measurements.

Abegaz and Awgichew (2009), in their study, state that linear sizes of animals could be used to estimate weight due to lack of accurate scale in the farm. They have explained how height at withers (HAW), heart girth (HG), body length (BDL), hip width (HW), rump height (RH), cannon bone length (CB), chest depth (CD) body parameters should be measured. It has been stated that animal moves and body positions may give error to the measurements and estimated weight, suggesting that to eliminate these effects, it is necessary to choose measurements less affected by body position of the animal if possible, to standardize positioning of all animals to be encountered and wait for animals to take an accurate position. Age determination is said to be important to decide when to purchase and sell, to determine the proper time for reproduction and to decide on suitable methods.

Tadesse and Gebremariam, (2010) in the study conducted to linearly estimate body weight of Highland sheep of Tigray region-North Ethiopia, 285 types of Highland sheep (206 female and 79 male) were used as materials. The animals were separated into two groups of gender as male-female and four groups of age. As a result of the measurement within the first age group goats, a significant correlation was found between heart girth ($r = 0.83$), body length ($r = 0.66$) and body weight ($p<0.001$). With more variables added to the correlation coefficient, there was an increase within the correlation coefficient. Heart girth parameter is one of the most fitted, easiest, cheapest parameters when estimating live weight in site conditions especially for small-scale farmers. At the end of the study, LW = -15.71 + 0.56 HG (R^2 = 0.69) was determined as the regression equation. Considering the current situation of this equation, it is believed to be appropriate to be practiced by farmers.

Sackey et al.(2013) conducted a study on Djallonke sheep at Livestock Research Institute Pokuase Station in which 47 animals were used in total and suggested that they could be used to estimate live weight by applying body measurements. Among the body parameters applied in this study were body length (BL) and chest depth (CD), neck girth (NG), abdominal periphery (AP), rump height (RH) and heart girth (HG). These parameters are stated to have been adapted to simple and multi-regression models evaluated with live weight and equation determination coefficient (R^2). It was found that heart girth, rump height and chest depth of female ones were significantly higher than those of male ones ($p<0.05$). It was put forward in this study that differences in body parameters between male and female sheep required adaptation of separate linear regression methods for genders. It was concluded that body sizes measurements such as heart girth and abdominal periphery could be used satisfactorily to measure live weight of Djallorike sheep at Livestock Research Institute Pokuase Station.

Shirzeyli et al. (2013), in their study conducted to determine the relation between body sizes and body weights in four races of Iranian sheep (Mehrbani, Zandi, Shaal and Macoei), body sizes including height and heart girth, body length and hip width were measured. It was stated that variance analysis and gender effect were significant in all races related to environmental factors and main effects ($p<0.05$). All main effects (height, heart girth, body length and hip width) are determined to have significant relation with body weight in four breeds. All body sizes studied demonstrated a high phenotypical correlation with body weight. It was found that body length that showed least correlation tendency with the body weight and its correlation coefficients were higher than 0.95. Besides, it was determined that correlation between body weight and heart girth in Mehrabani, Zandi and Macoei sheep races was fairly high (0.97, 0.97 and 0.94 respectively), while the related correlation in Shaal race was low (0.88). ıt was concluded that in Shaal sheep, withers height had high correlation with body weight (0.98) and that this correlation was lower in other races (0.91-0.93). It was found that in all of the four races hip width was determined to have the lowest phenotypical correlation (0.75 - 0.86) with body weight. In conclusion part of the study, it is stated that some of the body measurements could be used as accurate indicators to estimate body weight.

Mahmud et al. (2014) suggest that accurate measurement of live body weight which is hard in generally village conditions due to lack of weighing scales is a precondition to reach the very high goals often related to medical or economic status of the animals. It was concluded that animal body parameters that are calibrated properly under standard conditions are most accurate and consistent method to determine the body weight and that they could estimate live body weight of animals using linear body measurements. To determine the body weight of small ruminants, it is suggested that estimation models can be developed based on many real weight-linear measurement data such as body parameters (its heart girth, chest depth, body length, rump height, distance between eyes, ear length, ear width, ear thickness and tail length), weight tape (it is a tape used to measure specially marked heart girth and to transform it into live weight estimation), visual evaluation (this method is estimation of weight of animals without weighing tape). Heart girth is determined to be the most appropriate and reliable parameter among live weight estimations of sheep and goats.

Parés-Casanova et al., (2014) in their work used 145 animals (79 female and 66 male) of Chiapas type at different ages and Thoracic girth (chest girth) (TG), knee girth (front), fetlock girth, pastern (just under the knee), ankle girth and ear length measured. Thoracic girth was found to have at values of 0.847 related to stability factor (R^2) values calculated for the body. Chest girth is concluded to be a useful means to estimate body weight of native Chiapas sheep. It is found that to determine live weight from Thoracic girth, the equations LW (kg) = TG*0.730 for male Chiapas and LW (kg) = TG*0.696 for female Chiapas are satisfactory. It is shown that this simple formula does not demonstrate significant difference among real and estimated weight values.

Size and age of the sheep and goats are related to their productivity in general. Big-sized animals generally produce more meat than small ones. Size is represented with weight; however, other linear measurements can be applied as well. Size of an animal is a feature to be considered depending on age which allows the growth performance as a component to be evaluated in relation to decision on which animal should be purchased and sold. Accurately calibrated animal breeding scale is the most accurate and appropriate method to determine body weight. In ranch conditions where scales and registers are not available, it is hard to know weight and age of the sheep and goat. In addition to providing body size, linear measurements of animals can be used to calculate the weight. To estimate the age, it is possible to draw upon development of tooth of sheep and goat from the very beginning of the birth to the maturity. In the Mahmud et al., (2014)'s study made by Ethiopia Sheep and Goat Productivity Improvement Program (ESGPIP) titled "estimation of sheep and goat age", body weight, withers height, heart girth, chest depth, body length, rump height measurements of goats were estimated. Besides, live body weight was estimated using cannon bone length and other body linear measurements in Nigerian races of sheep.

3. MATERIAL AND METHODS

3.1. Material

3.1.1. Hair goats

Today goat breeding is a production branch which is becoming more important. According to FAO, the fact that world goat number rose from 464m to 880 m during 1980-2010 is indicator of the foregoing statement. According to 2014 data, there are 1 011 251 833 heads in the world (FAO, 2014). Distribution of the number of goats according to the continents is shown in Table 3.1. Though according to Turkish Statistical Institute data yearly goat number in Turkey (Hair and Angora) fluctuates between years 2000 and 2010 in particular, the number of goat between years 2016 and 1991 does not differ from each other so much (Table 3.2). The number of goat in Turkey is close to the number of goat in whole Europe. Statistical figures reveal how important goat breeding is in Turkey. This importance is clear given that number of goat is 35 640 927 heads in Americas, 16 534 309 heads in Europe and 10 344 936 heads in Turkey (Table 3.1). It is shown in Table 3.1 that regarding the ranking of goat numbers in the world continents Turkey has more goats than continent of Australia does (Table 3.1).

Table 3.1. Existence of goats in continents (FAO, 2014)

Continent	Number of Goats (heads)
Asia	580 703 222
Africa	374 380 445
America	35 640 927
Europe	16 534 309
Australia	3 992 930
Turkey	10 344 936
World	1 011 251 833

Table 3.2. Existence of goats in Turkey during 1991-2016

Years	Goats - Hair (heads)	Goats - Angora (heads)
1991	9 579 256	1 184 942
1992	9 439 600	1 014 340
1993	9 192 000	941 000
1994	8 767 000	797 000
1995	8 397 000	714 000
1996	8 242 000	709 000
1997	7 761 000	615 000
1998	7 523 000	534 000
1999	7 284 000	490 000
2000	6 828 000	373 000

2001	6 676 000	346 000
2002	6 519 332	260 762
2003	6 516 088	255 587
2004	6 379 900	230 037
2005	6 284 498	232 966
2006	6 433 744	209 550
2007	6 095 292	191 066
2008	5 435 393	158 168
2009	4 981 299	146 986
2010	6 140 627	152 606
2011	7 126 862	151 091
2012	8 199 184	158 102
2013	9 059 259	166 289
2014	10 167 125	177 811
2015	10 210 338	205 828
2016	10 137 534	207 765

The quality of goat meat and particularly goat milk plays a crucial role in attracting more attention in goat breeding in the world. Goat milk is distinctive as it is the closest milk to the breast milk among the consumable milk products. With **34** times more calcium content than breast milk and digestive system problems related to cow's milk, goat milk is considered more advantageous. This milk is valued as it is preferred more when dairy products are made through goat milk and some special products are produced depending on the milk. Given the goat milk deficit not only in Turkey but also in Europe and Middle East countries, it is essential to increase the capacity of production of goat milk. Contribution levels of goat milk production during 2012 and 2013 are given in.

In Turkey, ranked close to the top among world countries related to existence of goat within the framework of Native Goat Races, three main goat races, Ankara, Hair and Kilis, are bred. Apart from these, particularly in İzmir and İstanbul neighbourhoods a limited number of Maltese goat breeding is carried out.

3.1.2. The climatic and geographic structure of Siirt

This study was performed between 2015-2017 at Siirt University. Siirt Province is geographically located between 41˚-57' East longitude and 37˚-55' latitude. The Province is surrounded by Sırnak and Van provinces in the East, Batman in the West, Batman and Bitlis in the North and Şırnak and Mardin in the South. Dicle Valley and some of the city's mountains which are of great importance are located in the east of the town, and the highest point is 2838m. The highest valley called Cemikari (Botan valleys), and high mountains such as Ceman and Herekol are also situated within the borders of this town. The Southeastern mountains of the city are called Yassi and Şeyh Omar mountains. The streams and rivers within the province are namely Reşinan, Garzan, Kezer, Başur, Botan (Uluçay). The altitude of the city is between 600-1600m (Anonymous b, 2017).

Siirt Province with its wide pastures and plateaus is very suitable for cattle grazing. Animal breeding in the area is the main means of living. Mainly pasture animal breeding is performed in the city. However, livestock is not so developed here. There are especially small cattle such as sheep and goat bred. The people called nomads (göçer) generally deal with animal breeding in the region. These are the ones who do not settle in one area instead go to highlands in the summers, come back to their winter quarters in the winters, wandering around with their herds almost the whole year. The nomads, who spend the summers in Siirt, Bitlis, Hakkari, Van and Muş highlands and winters in some calmer places make use of the animal products they get to get profit in these towns. The dense population of nomads in Siirt causes an increase in the animal products in the area (Anonymous d, 2017).

Siirt has generally got a continental climate. The winter is very harsh in the northern and eastern parts and wet whereas in the southern and southwestern parts. Winters are mild however in the summers the province is very dry and hot. The average rainfall is about 698.6 mm. The hottest days in Siirt (on average 46.0 °C) are in August and the coldest days are in January (-19.3 °C). The average heat in the town is 15.9°C according to the last 60 years average. The average number of overcast days in the town is 60.5, clear days 154 and finally cloudy days 151,2. The average of relative humidity is % 51 and the months which has the highest rate of relative humidity are January and August with a percentage of % 70 (Anonymous c, 2017).

3.1.3. The animals used in the research

The material of the study was provided from a private farm. The data were collected from 81 female hair goats. Heart girth (HG), Body depth (BD), Body length (BL) and Live body weight (LBW) parameters were recorded after 8 hours of feed restriction. Body measurements were taken by a tape measure and body weight was taken using a digital scale (Chacon et al, 2011).

1. Heart Girth: is a circumferential measure taken around the chest just behind the front legs and withers. While the measurement, the animal kept stable and the accuracy of the reading of the meter was double checked.

Picture 3.1. Measuring the heart girth

2. Body Depth: For this parameter, the height between the very end of the goat's front leg and its back was measured. The stability of the goat is very important during these measurement processes.

Picture 3.2. Measuring the body depth

3. Body Length: refers to the distance from the base of the ear to the base of the tail. It can also be measured as the distance from base of tail to the base of neck (first thoracic vertebrae), or to front of the chest or to tip of the nose (Mahmud et al, 2014).

Picture 3.3. Measuring the body length

4. Body Weight: The goat which body parameters were measured was weighed according to its body weight by digital scale and the values were noted down.

Picture 3.4. Measuring the body weight

3.2. Method

3.2.1. Fuzzy logic

Experts usually rely on common sense when they solve problems. They also use vague and ambiguous terms. For example, an expert might say, 'Though the power transformer is slightly overloaded, I can keep this load for a while'. Other experts have no difficulties with understanding and interpreting this statement because they have the background to hearing problems described like this. However, a knowledge engineer would have difficulties providing a computer with the same level of understanding (Negnevitsky, 2005).

Fuzzy logic is not logic that is fuzzy, but logic that is used to describe fuzziness. Fuzzy logic is the theory of fuzzy sets, sets that calibrate vagueness. Fuzzy logic is based on the idea that all things admit of degrees. Temperature, height, speed, distance, beauty - all come on a sliding scale. The motor is running really hot. Electric cars are not very fast. High-performance drives require very rapid dynamics and precise regulation. Sydney is a beautiful city. Such a sliding scale often makes it impossible to distinguish members of a class from non-members.

Boolean or conventional logic uses sharp distinctions. It forces us to draw lines between members of a class and non-members. It makes us draw lines in the sand. For instance, we may say, 'The maximum range of an electric vehicle is short', regarding a range of 300 km or less as short, and a range greater than 300 km as long. By this standard, any electric vehicle that can cover a distance of 301km (or 300 km and 500 m or even 300 km and 1 m) would be described as long-range. Similarly, we say Tom is tall because his height is 181 cm. If we drew a line at 180 cm, we would find that David, who is 179 cm, is small. Is David really a small man or have we just drawn an arbitrary line in the sand? Fuzzy logic makes it possible to avoid such absurdities.

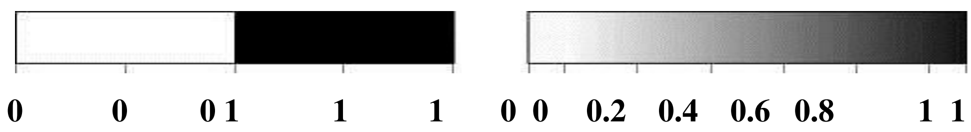
Fuzzy logic reflects how people think. It attempts to model our sense of words, our decision making and our common sense. As a result, it is leading to new, more human, intelligent systems.

Fuzzy, or multi-valued logic was introduced in the 1930s by Jan Lukasiewicz, a Polish logician and philosopher (Lukasiewicz, 1930). He studied the mathematical representation of fuzziness based on such terms as tall, old and hot. While classical logic operates with only two values 1 (true) and 0 (false), Lukasiewicz introduced logic that extended the range of truth values to all real numbers in the interval between 0 and 1. He used a number in this interval to represent the possibility that a given statement was true or false. For example, the possibility that a man 181 cm tall is really tall might be set to a value of 0.86. It is likely that the man is tall. This work led to an inexact reasoning technique often called possibility theory.

Later, in 1937, Max Black, a philosopher, published a paper called 'Vagueness:

an exercise in logical analysis' (Black, 1937). In this paper, he argued that a continuum implies degrees. Imagine, he said, a line of countless 'chairs'. At one end is a Chippendale. Next to it is a near-Chippendale, in fact indistinguishable from the first item. Succeeding 'chairs' are less and less chair-like, until the line ends with a log. When does a chair become a log? The concept chair does not permit us to draw a clear line distinguishing chair from not-chair. Max Black also stated that if a continuum is discrete, a number can be allocated to each element. This number will indicate a degree. But the question is degree of what. Black used the number to show the percentage of people who would call an element in a line of 'chairs' a chair; in other words, he accepted vagueness as a matter of probability. However, Black's most important contribution was in the paper's appendix. Here he defined the first simple fuzzy set and outlined the basic ideas of fuzzy set operations (Negnevitsky, 2005).

In 1965 Lotfi Zadeh, Professor and Head of the Electrical Engineering Department at the University of California at Berkeley, published his famous paper 'Fuzzy sets'. In fact, Zadeh discovered fuzziness, identified and explored it, and promoted and fought for it. Zadeh extended the work on possibility theory into a formal system of mathematical logic, and even more importantly, he introduced a new concept for applying natural language terms. This new logic for representing and manipulating fuzzy terms was called fuzzy logic, and Zadeh became the Master of fuzzy logic. As Zadeh said, the term of fuzzy is concrete, immediate and descriptive; we all know what it means. However, many people in the West were repelled by the word fuzzy, because



(a) (b)

it is usually used in a negative sense.

Figure 3.1. Range of logical values in Boolean and fuzzy logic: (a) Boolean logic; (b) fuzzy logic

Fuzziness rests on fuzzy set theory, and fuzzy logic is just a small part of that theory. However, Zadeh used the term fuzzy logic in a broader sense (Zadeh, 1965):

Fuzzy logic is determined as a set of mathematical principles for knowledge representation based on degrees of membership rather than on crisp membership of classical binary logic.

Unlike two-valued Boolean logic, fuzzy logic is multi-valued. It deals with degrees of membership and degrees of truth. Fuzzy logic uses the continuum of logical values between 0 (completely false) and 1 (completely true). Instead of just black and white, it employs the spectrum of colours, accepting that things can be partly true and partly false at the same time. As can be seen in Figure 3.1, fuzzy logic adds a range of logical values to Boolean logic. Classical binary logic now can be considered as a special case of multi-valued fuzzy logic.

3.2.2. Fuzzy sets

The concept of a set is fundamental to mathematics. However, our own language is the supreme expression of sets. For example, *car* indicates the set of cars. When we say *a car,* we mean one out of the set of cars.

Let *X* be a classical (crisp) set and *x* an element. Then the element *x* either belongs to *X* ($x \in X$) or does not belong to *X* ($x \notin X$). That is, classical set theory imposes a sharp boundary on this set and gives each member of the set the value of 1, and all members that are not within the set a value of 0.

Crisp set theory is governed by a logic that uses one of only two values: true or false. This logic cannot represent vague concepts, and therefore fails to give the answers on the paradoxes. The basic idea of the fuzzy set theory is that an element belongs to a fuzzy set with a certain degree of membership. Thus, a proposition is not either true or false, but may be partly true (or partly false) to any degree. This degree is usually taken as a real number in the interval [0,1].

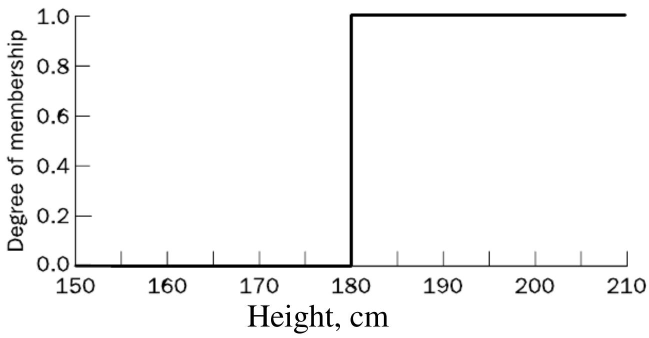
The classical example in the fuzzy set theory is *tall men.* The elements of the fuzzy set 'tall men' are all men, but their degrees of membership depend on their height, as shown in Table 3.3. Suppose, for example, Mark at 205 cm tall is given a degree of 1, and Peter at 152 cm is given a degree of 0. All men of intermediate height have intermediate degrees. They are partly tall. Obviously, different people may have different views as to whether a given man should be considered as tall. However, our candidates for *tall men* could have the memberships presented in Table 3.3.

Table 3.3. Degree of membership of ‘tall men’

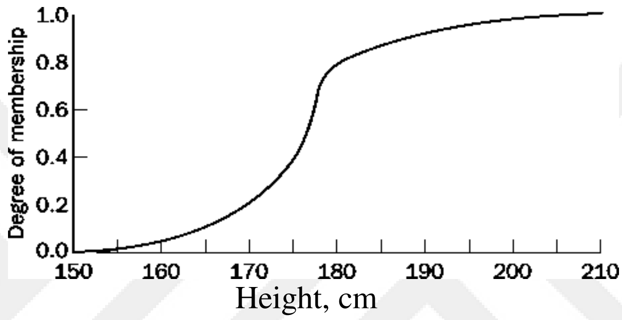
Name	Height, cm	Degree of membership	
		Crisp	Fuzzy
Chris	208	1	1.00
Mark	205	1	1.00
John	198	1	0.98
Tom	181	1	0.82
David	179	0	0.78
Mike	172	0	0.24
Bob	167	0	0.15
Steven	158	0	0.06
Bill	155	0	0.01
Peter	152	0	0.00

It can be seen that the crisp set asks the question, 'Is the man tall?' and draws a line at, say, 180 cm. *Tall men* are above this height and *not tall men* below. In contrast, the fuzzy set asks, 'How tall is the man?' The answer is the partial membership in the fuzzy set, for example, Tom is 0.82 tall. A fuzzy set is capable of providing a graceful transition across a boundary, as shown in Figure 3.2. We might consider a few other sets such as 'very short men', 'short men', 'average men' and 'very tall men'.

In Figure 3.2 the horizontal axis represents the universe of discourse - the range of all possible values applicable to a chosen variable. In our case, the variable is the human height. According to this representation, the universe of men's heights consists of all tall men. However, there is often room for discretion, since the context of the universe may vary. For example, the set of 'tall men' might be part of the universe of human heights or mammal heights, or even all the vertical axis in Figure 3.2 represents the membership value of the fuzzy set. In our case, the fuzzy set of 'tall men' maps height values into corresponding membership values. As can be seen from Figure 3.2, David who is 179 cm tall, which is just 2 cm less than Tom, no longer suddenly becomes a *not tall* (or *short)* man (as he would in crisp sets). Now David and other men are gradually removed from the set of 'tall men' according to the decrease of their heights.



(a)



(b)

Figure 3.2. Crisp (a) and fuzzy (b) sets of 'tall men'

A fuzzy set can be simply defined as a set with fuzzy boundaries.

Let X be the universe of discourse and its elements be denoted as x. In classical set theory, crisp set A of X is defined as function f_A (x) called the characteristic function of A

$$f_A(x) : \mathrm{X} \rightarrow 0, 1$$

where,

$$f_A(x) = \begin{cases} 1, & if \quad x \in A \\ 0, & if \quad x \notin A \end{cases}$$

This set maps universe X to a set of two elements. For any element x of universe X, characteristic function f_A (x) is equal to 1 if x is an element of set A, and is equal to 0 if x is not an element of A.

In the fuzzy theory, fuzzy set A of universe X is defined by function μ_A (x) called the membership function of set A

$$\mu_A \text{ (x)} : \mathrm{X} \rightarrow [0, 1]$$

where,

μ_A (x) = 1 if x is totally in A;

μ_A (x) = 0 if x is not in A;

$0 < \mu_A(x) < 1$ if x is partly in A.

This set allows a continuum of possible choices. For any element x of universe X, membership function μ_A (x) equals the degree to which x is an element of set A. This degree, a value between 0 and 1, represents the degree of membership, also called membership value, of element x in set A.

The membership function must be determined first. A number of methods learned from knowledge acquisition can be applied here. For example, one of the most practical approaches for forming fuzzy sets relies on the knowledge of a single expert. The expert is asked for his or her opinion whether various elements belong to a given set. Another useful approach is to acquire knowledge from multiple experts. A new technique to form fuzzy sets was recently introduced. It is based on artificial neural networks, which learn available system operation data and then derive the fuzzy sets automatically.

After acquiring the knowledge for men's heights, we could produce a fuzzy set of *tall men.* In a similar manner, we could obtain fuzzy sets of *short* and *average* men. These sets are shown in Figure 3.3, along with crisp sets. The universe of discourse - the men's heights - consists of three sets: *short, average* and *tall men.* In fuzzy logic, as you can see, a man who is 184 cm tall is a member of the *average men* set with a degree of membership of 0.1, and at the same time, he is also a member of the *tall men* set with a degree of 0.4. This means that a man of 184 cm tall has partial membership in multiple sets.

Now assume that universe of discourse *X*, also called the reference super set, is a crisp set containing five elements $X = \{x_1,x_2,x_3,x_4,x_5\}$. Let *A* be a crisp subset of *X* and assume that *A* consists of only two elements, $A = \{x_2, x_3\}$. Subset *A* can now be described by $A = \{(x_1, 0), (x_2,1), (x_3,1), (x_4,0), (x_5,0)\}$, i.e. as a set of pairs $\{(x_i, \mu_A(x_i)\}$, where $\mu_A(x_i)$ is the membership function of element x_i in the subset *A*. The question is whether μ_A (x) can take only two values, either 0 or 1, or any value between 0 and 1. It was also the basic question in fuzzy sets examined by Lotfi Zadeh in 1965 (Zadeh, 1965).

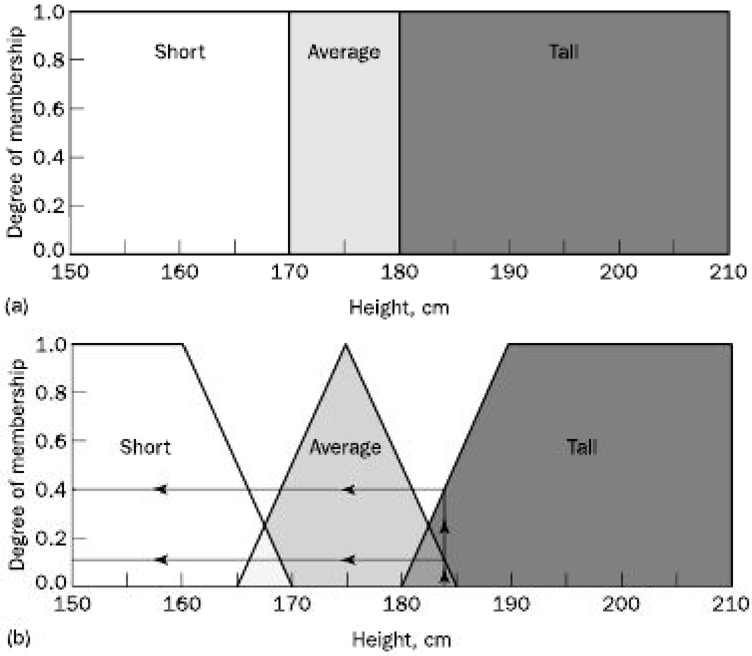


Figure 3.3. Crisp (a) and fuzzy (b) sets of short, average and tall men

If X is the reference super set and A is a subset of X, then A is said to be a fuzzy subset of X if, and only if,

$$A = \{(x, \mu_A(x)\} \qquad x \in X,\ \mu_A(x): X \rightarrow [0,1]$$

In a special case, when $X \rightarrow \{0,1\}$ is used instead of $X \rightarrow [0,1]$, the fuzzy subset A becomes the crisp subset A.

Fuzzy and crisp sets can be also presented as shown in Figure 3.4.

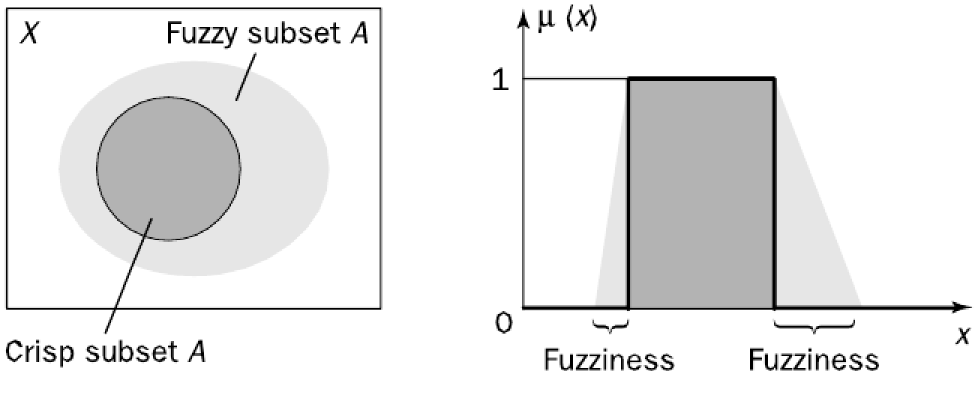


Figure 3.4. Representation of crisp and fuzzy subset of X

Fuzzy subset A of the finite reference super set X can be expressed as,

$$A = \{(x_1, \mu_A(x_1)\}, \{(x_2, \mu_A(x_2)\}, \ldots, \{\{x_n, \mu_A\{x_n)\}$$

However, it is more convenient to represent A as,

$$A = \{\mu_A(x_1)/x_1\}, \{\mu_A(x_2)/x_2\}, \ldots, \{\mu_A(x_n)/x_n\},$$

where the separating symbol / is used to associate the membership value with its coordinate on the horizontal axis.

To represent a continuous fuzzy set in a computer, we need to express it as a function and then to map the elements of the set to their degree of membership. Typical functions that can be used are sigmoid, gaussian and pi. These functions can represent the real data in fuzzy sets, but they also increase the time of computation. Therefore, in practice, most applications use linear fit functions similar to those shown in Figure 3.3. For example, the fuzzy set of *tall men* in Figure 3.3 can be represented as a fit-vector,

tall men — (0/180, 0.5/185, 1/190) or

tall men — (0/180, 1/190)

Fuzzy sets of *short* and *average men* can be also represented in a similar manner,

short men — (1/160, 0.5/165, 0/170) or

short men — (1/160, 0/170)

average men — (0/165, 1/175, 0/185)

3.2.3. Linguistic variables and hedges

At the root of fuzzy set theory lies the idea of linguistic variables. A linguistic variable is a fuzzy variable. For example, the statement 'John is tall' implies that the linguistic variable *John* takes the linguistic value *tall.* In fuzzy expert systems, linguistic variables are used in fuzzy rules. For example,

IF wind is strong
THEN sailing is good

IF project _duration is long
THEN completion _risk is high

IF speed is slow
THEN stopping_ distance is short

The range of possible values of a linguistic variable represents the universe of discourse of that variable. For example, the universe of discourse of the linguistic variable *speed* might have the range between 0 and 220 km per hour and may include such fuzzy subsets as *very slow, slow, medium, fast,* and *very fast.* Each fuzzy subset also represents a linguistic value of the corresponding linguistic variable.

A linguistic variable carries with it the concept of fuzzy set qualifiers, called hedges. Hedges are terms that modify the shape of fuzzy sets. They include adverbs such as *very, somewhat, quite, more or less* and *slightly.* Hedges can modify verbs, adjectives, adverbs or even whole sentences. They are used as

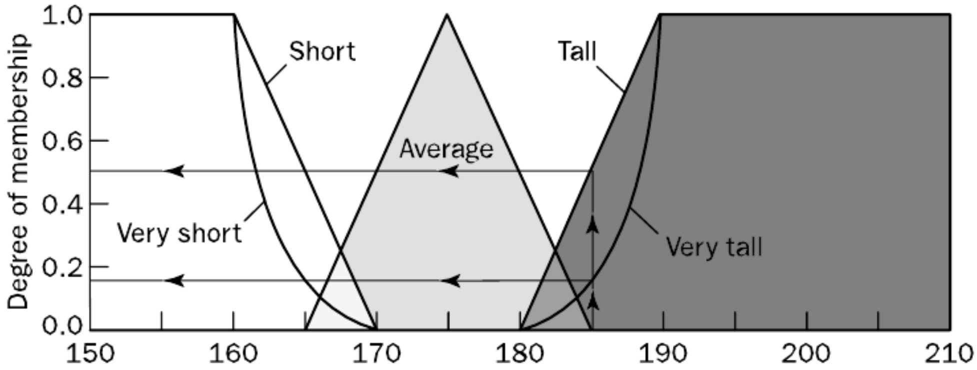
- All-purpose modifiers, such as *very, quite* or *extremely.*
- Truth-values, such as *quite true* or *mostly false.*
- Probabilities, such as *likely* or *not very likely.*
- Quantifiers, such as *most*, *several* or *few*.
- *Possibilities, such as almost impossible or quite possible.*

Hedges act as operations themselves. For instance, *very* performs concentration and creates a new subset. From the set of *tall men*, it derives the subset of *very tall men*. *Extremely* serves the same purpose to a greater extent.

An operation opposite to concentration is dilation. It expands the set. *More or less* performs dilation; for example, the set of *more or less tall men* is broader than the set of *tall men.*

Hedges are useful as operations, but they can also break down continuums into fuzzy intervals. For example, the following hedges could be used to describe temperature: *very cold, moderately cold, slightly cold, neutral, slightly hot, moderately hot* and *very hot.* Obviously these fuzzy sets overlap. Hedges help to reflect human thinking, since people usually cannot distinguish between *slightly hot* and *moderately hot*.

Figure 3.5 illustrates an application of hedges. The fuzzy sets shown previously in Figure 3.3 are now modified mathematically by the hedge *very.* Consider, for example, a man who is 185 cm tall. He is a member of the *tall men* set with a degree of membership of 0.5. However, he is also a member of the set of *very tall men* with a degree of 0.15, which is *fairly* reasonable.



Height, cm

Figure 3.5. Fuzzy sets with *very* hedge

Consider the hedges often used in practical applications.

- *Very,* the operation of concentration, as we mentioned above, narrows a set down and thus reduces the degree of membership of fuzzy elements. This operation can be given as a mathematical square:

$$\mu_A^{very}(x) = [\mu_A(x)]^2$$

Hence, if Tom has a 0.86 membership in the set of *tall men,* he will have a 0.7396 membership in the set of *very tall men.*

- *Extremely* serves the same purpose as *very,* but does it to a greater extent. This operation can be performed by raising $\mu_A(x)$ to the third power:

$$\mu_A^{extremely}(x) = [\mu_A(x)]^3$$

If Tom has a 0.86 membership in the set of *tall men,* he will have a 0.7396 membership in the set of *very tall men* and 0.6361 membership in the set of *extremely tall men.*

- *Very very* is just an extension of concentration. It can be given as a square of the operation of concentration:

$$\mu_A^{very\ very}(x) = [\mu_A^{very}(x)]^2 = [\mu_A(x)]^4$$

For example, Tom, with a 0.86 membership in the *tall men set* and a 0.7396 membership in the *very tall men set,* will have a membership of 0.5470 in the set of *very very tall men.*

- *More or less,* the operation of dilation, expands a set and thus increases the degree of membership of fuzzy elements. This operation is presented as:

$$\mu_A^{\text{more or less}}(x) = \sqrt{\mu_A(x)}$$

Hence, if Tom has a 0.86 membership in the set of *tall men,* he will have a 0.9274 membership in the set of *more or less tall men.*

- *Indeed,* the operation of intensification, intensifies the meaning of the whole sentence. It can be done by increasing the degree of membership above 0.5 and decreasing those below 0.5. The hedge *indeed* may be given by either:

$$\mu_A^{indeed}(x) = 2[\mu_A(x)]^2 \qquad \text{if } \; 0 \leq \mu_A(x) \leq 0.5$$

or

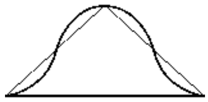
$$\mu_A^{indeed}(x) = 1 - 2[1 - \mu_A(x)]^2 \qquad \text{if } \; 0.5 < \mu_A(x) \leq 1$$

If Tom has a 0.86 membership in the set of *tall men*, he can have a 0.9608 membership in the set of *indeed tall men.* In contrast, Mike, who has a 0.24 membership in *tall men* set, will have a 0.1152 membership in the *indeed tall men* set.

Table 3.4. Representation of hedges in fuzzy logic

Hedge	Mathematical expression	Graphical representation
A little	$[\mu_A(x)]^{1.3}$	
Slightly	$[\mu_A(x)]^{1.7}$	
Very	$[\mu_A(x)]^{2}$	
Extremely	$[\mu_A(x)]^{3}$	
Very very	$[\mu_A(x)]^{4}$	
More or less	$\sqrt{\mu_A(x)}$	
Somewhat	$\sqrt{\mu_A(x)}$	

Indeed $\begin{cases} 2[\mu_A(x)]^2 & \text{if } 0 \le \mu_A(x) \le 0.5 \\ 1 - 2[1 - \mu_A(x)]^2 & \text{if } 0.5 < \mu_A(x) \le 1 \end{cases}$



Mathematical and graphical representations of hedges are summarized in Table 3.4.

3.2.4. Operations of fuzzy sets

The classical set theory developed in the late 19th century by Georg Cantor describes how crisp sets can interact. These interactions are called operations.

Cantor's sets

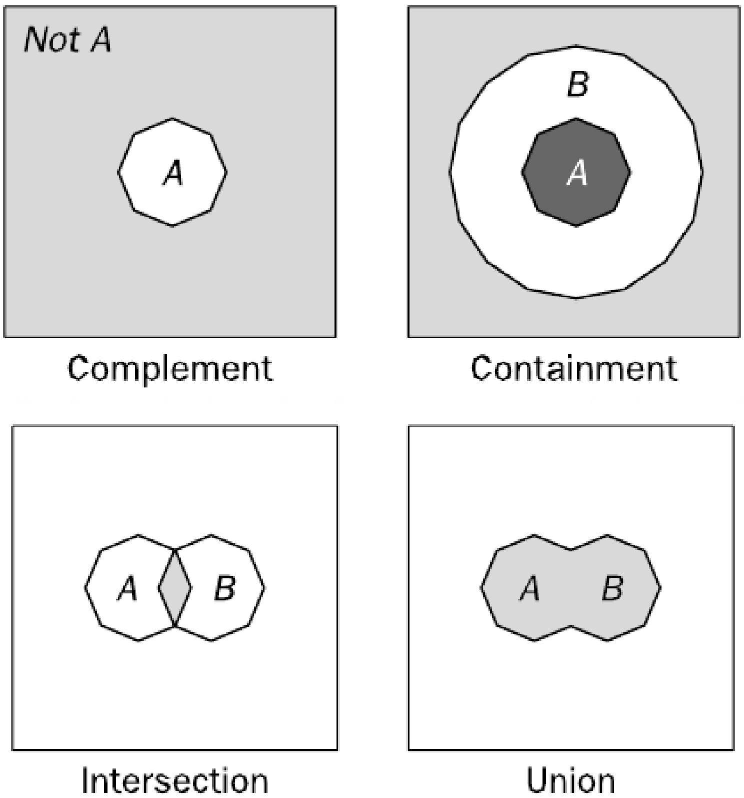


Figure 3.6. Operations on classical sets

We look at four of them: complement, containment, intersection and union. These operations are presented graphically in Figure 3.6. Let us compare operations of classical and fuzzy sets.

Complement

- ✓ Crisp sets: Who does not belong to the set?
- ✓ Fuzzy sets: How much do elements not belong to the set?

The complement of a set is an opposite of this set. For example, if we have the set of *tall men,* its complement is the set of *NOT tall men.* When we remove the tall men set from the universe of discourse, we obtain the complement. If *A* is the fuzzy set, its complement -A can be found as follows:

$$\mu_{-A}(x) = 1 - \mu_A(x)$$

For example, if we have a fuzzy set of *tall men*, we can easily obtain the fuzzy set of *NOT tall men*:

tall men = (0/180,0.25/182.5,0.5/185,0.75/187.5,1/190)

NOT tall men = (1/180,0.75/182.5,0.5/185,0.25/187.5,0/190)

Containment

- ✓ Crisp sets: Which sets belong to which other sets?
- ✓ Fuzzy sets: Which sets belong to other sets?

Similar to a Chinese box or Russian doll, a set can contain other sets. The smaller set is called the subset. For example, the set of *tall men* contains all tall men. Therefore, *very tall men* is a subset of *tall men.* However, the *tall men* set is just a subset of the set of *men.* In crisp sets, all elements of a subset entirely belong to a larger set and their membership values are equal to 1. In fuzzy sets, however, each element can belong less to the subset than to the larger set. Elements of the fuzzy subset have smaller memberships in it than in the larger set.

tall men = (0/180,0.25/182.5,0.50/185,0.75/187.5,1/190)

very tall men = (0/180,0.06/182.5,0.25/185,0.56/187.5,1/190)

Intersection

- ✓ Crisp sets: Which element belongs to both sets?
- ✓ Fuzzy sets: How much of the element is in both sets?

In classical set theory, an intersection between two sets contains the elements shared by these sets. If we have, for example, the set of *tall men* and the set of *fat men,* the intersection is the area where these sets overlap, i.e. Tom is in the intersection only if he is tall AND fat. In fuzzy sets, however, an element may partly belong to both sets with different memberships. Thus, a fuzzy intersection is the lower membership in both sets of each element.

The fuzzy operation for creating the intersection of two fuzzy sets *A* and *B* on universe of discourse *X* can be obtained as:

$$\mu_{A\cap B}(x) = \min\,[\mu_A(x), \mu_B(x)] = \mu_A(x) \cap \mu_B(x), \qquad \text{where } x \in X$$

Consider, for example, the fuzzy sets of *tall* and *average men:*

$$\textit{tall men} = (0/165, 0/175, 0.0/180, 0.25/182.5, 0.5/185, 1/190)$$

$$\textit{average men} = (0/165, 1/175, 0.5/180, 0.25/182.5, 0.0/185, 0/190)$$

According to the equation above, the intersection of these two sets is

$$\textit{tall men} \cap \textit{average men} = (0/165, 0/175, 0/180, 0.25/182.5, 0/185, 0/190)$$

or

$$\textit{tall men} \cap \textit{average men} = (0/180, 0.25/182.5, 0/185)$$

This solution is represented graphically in Figure 3.3.

Union

- ✓ Crisp sets: Which element belongs to either set?
- ✓ Fuzzy sets: How much of the element is in either set?

The union of two crisp sets consists of every element that falls into either set. For example, the union of *tall men* and *fat men* contains all men who are tall OR fat, i.e. Tom is in the union since he is tall, and it does not matter whether he is fat or not. In fuzzy sets, the union is the reverse of the intersection. That is, the union is the largest membership value of the element in either set.

The fuzzy operation for forming the union of two fuzzy sets *A* and *B* on universe *X* can be given as:

$$\mu_{A \cup B}(x) = \max\,[\mu_A(x), \mu_B(x)] = \mu_A(x) \cup \mu_B(x), \qquad \text{where } x \in X$$

Consider again the fuzzy sets of *tall* and *average* men:

$$\textit{tall men} = (0/165, 0/175, 0.0/180, 0.25/182.5, 0.5/185, 1/190)$$

$$\textit{average men} = (0/165, 1/175, 0.5/180, 0.25/182.5, 0.0/185, 0/190)$$

The union of these two sets is

$$\textit{tall men} \cup \textit{average men} = (0/165, 1/175, 0.5/180, 0.25/182.5, 0.5/185, 1/190)$$

Diagrams for fuzzy set operations are shown in Figure 3.7.

Crisp and fuzzy sets have the same properties; crisp sets can be considered as just a special case of fuzzy sets. Frequently used properties of fuzzy sets are described below.

Commutativity

$$A \cup B = B \cup A$$
$$A \cap B = B \cap A$$

Example:

tall men OR short men = short men OR tall men
tall men AND short men = short men AND tall men

Associativity

$$A \cup (B \cup C) = (A \cup B) \cup C$$
$$A \cap (B \cap C) = (A \cap B) \cap C$$

Fuzzy sets

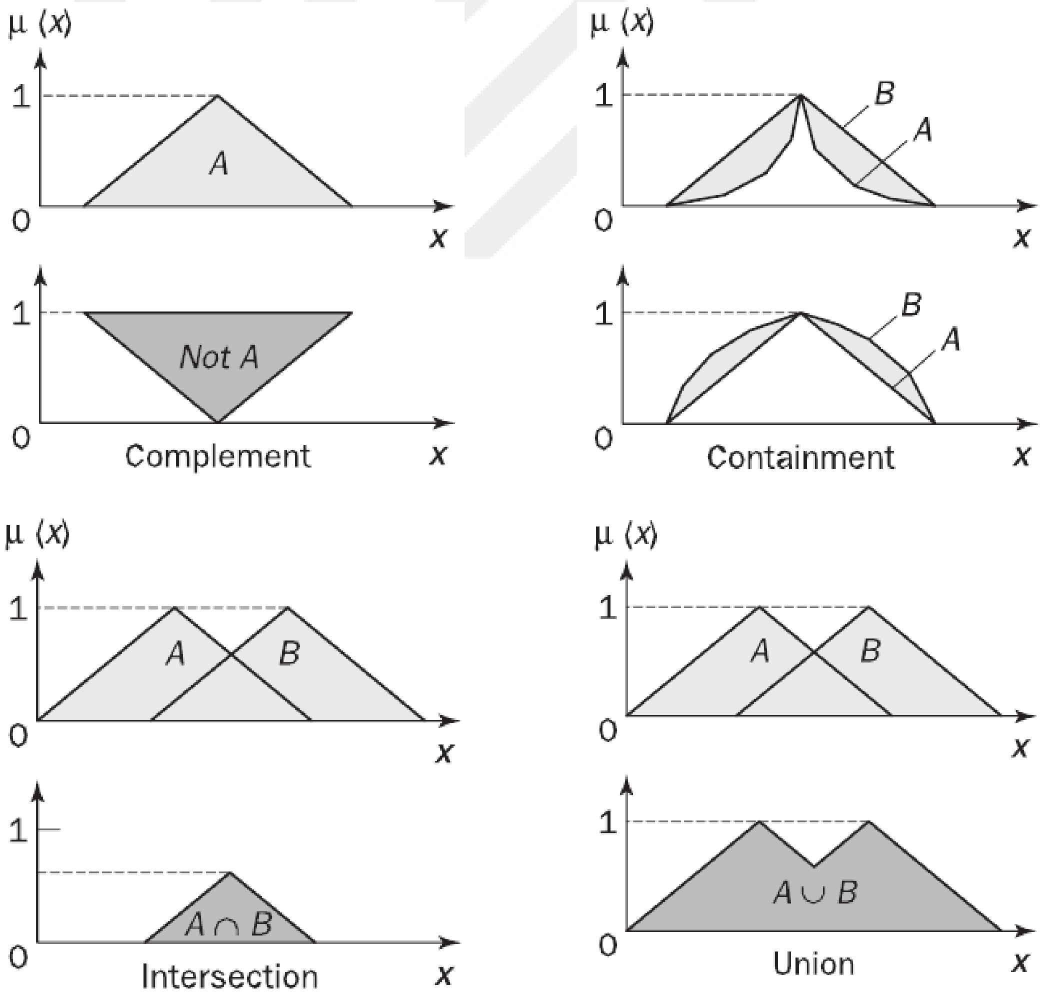


Figure 3.7. Operations of fuzzy sets

Example:

tall men OR (short men OR average men) = (tall men OR short men) OR average men

tall men AND (short men AND average men) = (tall men AND short men) AND average men

Distributivity

$$A \cup (B \cap C) = (A \cup B) \cap (A \cup C)$$

$$A \cap (B \cup C) = (A \cap B) \cup (A \cap C)$$

Example:

tall men OR (short men AND average men) = (tall men OR short men) AND (tall men OR average men)

tall men AND (short men OR average men) = (tall men AND short men) OR (tall men AND average men)

Idempotency

$$A \cup A = A$$

$$A \cap A = A$$

Example:

tall men OR tall men — tall men

tall men AND tall men — tall men

Identity

$$A \cup \varnothing = A$$

$$A \cap X = A$$

$$A \cap \varnothing = \varnothing$$

$$A \cup X = X$$

Example:

tall men OR undefined = tall men

tall men AND unknown = tall men

tall men AND undefined = undefined

tall men OR unknown = unknown

where *undefined* is an empty (null) set, the set having all degree of memberships equal to 0, and *unknown* is a set having all degree of memberships equal to 1.

Involution

$$\neg(\neg A) = A$$

Example:

NOT (NOT tall men) = tall men

Transitivity

If $(A \subset B) \cap (B \subset C)$ then $A \subset C$

Every set contains the subsets of its subsets.

Example:

IF (extremely tall men ⊂ very tall men) AND (very tall men ⊂ tall men) THEN (extremely tall men ⊂ tall men)

De Morgan's Laws

$$\neg(A \cap B) = \neg A \cup \neg B$$

$$\neg(A \cup B) = \neg A \cap \neg B$$

NOT (tall men AND short men) = NOT tall men OR NOT short men

NOT (tall men OR short men) = NOT tall men AND NOT short men

Using fuzzy set operations, their properties and hedges, we can easily obtain a variety of fuzzy sets from the existing ones. For example, if we have fuzzy set *A* of *tall men* and fuzzy set *B* of *short men,* we can derive fuzzy set *C* of *not very tall men and not very short men* or even set *D* of *not very very tall and not very very short men* from the following operations:

$$\mu_C(x) = [1 - \mu_A(x)^2] \cap [1 - (\mu_B(x)^2]$$

$$\mu_D(x) = [1 - \mu_A(x)^4] \cap [1 - (\mu_B(x)^4]$$

Generally, we apply fuzzy operations and hedges to obtain fuzzy sets which can represent linguistic descriptions of our natural language.

3.2.5. Fuzzy rules

In 1973, Lotfi Zadeh published his second most influential paper (Zadeh, 1973).

This paper outlined a new approach to analysis of complex systems, in which Zadeh suggested capturing human knowledge in fuzzy rules. A fuzzy rule can be defined as a conditional statement in the form:

IF x is A
THEN y is B

where x and y are linguistic variables; and A and B are linguistic values determined by fuzzy sets on the universe of discourses X and Y, respectively.

A classical IF-THEN rule uses binary logic, for example,

Rule: 1
IF speed is > 100
THEN stopping_distance is long

Rule: 2
IF speed is < 40
THEN stopping_distance is short

The variable speed can have any numerical value between 0 and 220 km/h, but the linguistic variable *stopping_distance* can take either value *long* or *short.* In other words, classical rules are expressed in the black-and-white language of Boolean logic. However, we can also represent the stopping distance rules in a fuzzy form:

Rule: 1
IF speed is fast
THEN stopping _distance is long

Rule: 2
IF speed is slow
THEN stopping _distance is short

Here the linguistic variable *speed* also has the range (the universe of discourse) between 0 and 220 km/h, but this range includes fuzzy sets, such as *slow, medium* and *fast.* The universe of discourse of the linguistic variable *stopping_distance* can be between 0 and 300 m and may include such fuzzy sets as *short, medium* and *long*. Thus fuzzy rules relate to fuzzy sets.

Fuzzy expert systems merge the rules and consequently cut the number of rules by at least 90 percent.

Fuzzy reasoning includes two distinct parts: evaluating the rule antecedent (the IF part of the rule) and *implication* or applying the result to the consequent (the THEN part of the rule).

In classical rule-based systems, if the rule antecedent is true, then the consequent is also true. In fuzzy systems, where the antecedent is a fuzzy statement, all rules fire to some extent, or in other words they fire partially. If the antecedent is true to some degree of membership, then the consequent is also true to that same degree.

Consider, for example, two fuzzy sets, 'tall men' and 'heavy men' represented in Figure 3.8.

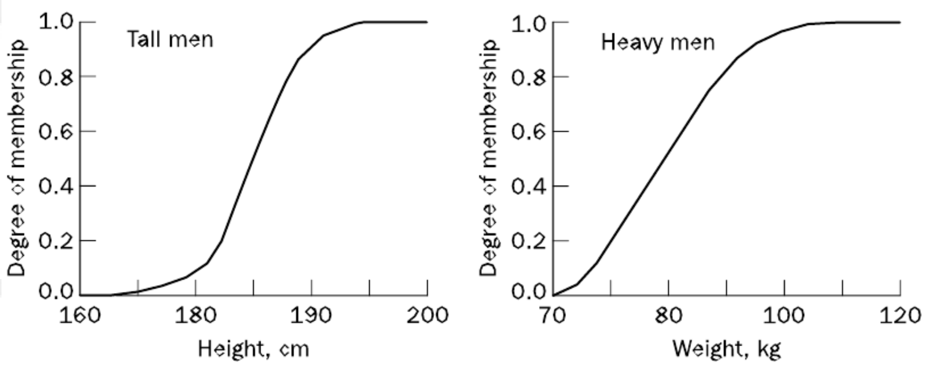


Figure 3.8. Fuzzy sets of *tall* and *heavy* men

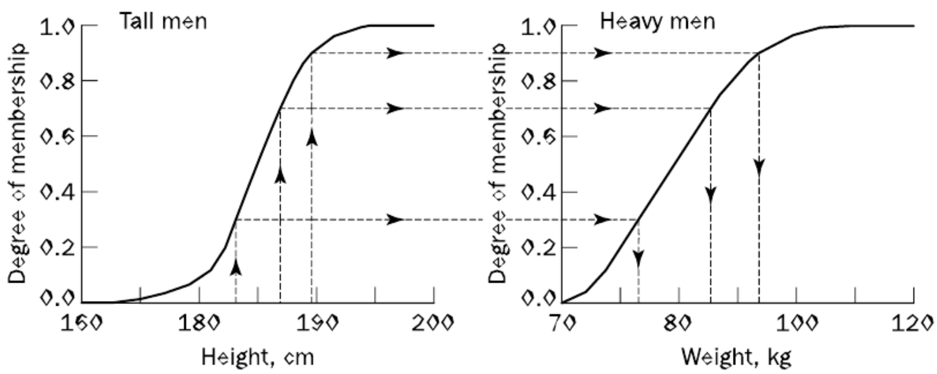


Figure 3.9. Monotonic selection of values for man weight

These fuzzy sets provide the basis for a weight estimation model. The model is based on a relationship between a man's height and his weight, which is expressed as a single fuzzy rule:

IF height is *tall*

THEN   weight is *heavy*

The value of the output or a truth membership grade of the rule consequent can be estimated directly from a corresponding truth membership grade in the antecedent (Cox, 1999). This form of fuzzy inference uses a method called monotonic selection. Figure 3.9 shows how various values of men's weight are derived from different values for men's height. As a production rule, a fuzzy rule can have multiple antecedents, for example:

IF   Project _duration is long
AND   Project _staffing is large
AND   Project _funding is
THEN   risk is high

IF   service is excellent
OR   food is delicious
THEN   tip is generous

All parts of the antecedent are calculated simultaneously and resolved in a single number, using fuzzy set operations considered in the previous section. The consequent of a fuzzy rule can also include multiple parts, for instance:

IF   temperature is hot
THEN   hot _water is reduced;
    cold _water is increased

In this case, all parts of the consequent are affected equally by the antecedent. In general, a fuzzy expert system incorporates not one but several rules that describe expert knowledge and play off one another. The output of each rule is a fuzzy set, but usually we need to obtain a single number representing the expert system output. In other words, we want to get a precise solution, not a fuzzy one. To obtain a single crisp solution for the output variable, a fuzzy expert system first aggregates all output fuzzy sets into a single output fuzzy set, and then defuzzifies the resulting fuzzy set into a single number.

3.2.6. Fuzzy inference

Fuzzy inference can be defined as a process of mapping from a given input to an output, using the theory of fuzzy sets.

3.2.6.1. Mamdani-style inference

The most commonly used fuzzy inference technique is the so-called Mamdani method. In 1975, Professor Ebrahim Mamdani of London University built one of the first fuzzy systems to control a steam engine and boiler combination (Mamdani and Assilian, 1975). He applied a set of fuzzy rules supplied by experienced human operators.

The Mamdani-style fuzzy inference process is performed in four steps: fuzzification of the input variables, rule evaluation, aggregation of the rule outputs, and finally defuzzification.

To see how everything fits together, we examine a simple two-input one-output problem that includes three rules:

Rule: 1	Rule: 1
IF x is A3	*IF project _funding is adequate*
OR y is *B1*	*OR project _staffing is small*
THEN z is C1	THEN *risk* is *low*
Rule: 2	Rule: 2
IF x is A2	*IF project _funding is marginal*
AND y is *B*2	*AND project _staffing is large*
THEN z is *C*2	*THEN risk is normal*
Rule: 3	Rule: 3
IF x is A1	*IF project_funding is inadequate*
THEN z is *C*3	*THEN risk is high*

where x, *y* and *z (project funding, project staffing* and *risk)* are linguistic variables; A1, A2 and A3 *(inadequate, marginal* and *adequate)* are linguistic values determined by fuzzy sets on universe of discourse *X (project funding); B1* and *B2 (small* and *large)* are linguistic values determined by fuzzy sets on universe of discourse *Y (project staffing); Cl, C2* and C3 (low, *normal* and *high)* are linguistic values determined by fuzzy sets on universe of discourse *Z (risk).*

The basic structure of Mamdani-style fuzzy inference for the problem is shown in Figure 3.10.

Step 1: ***Fuzzification***

The first step is to take the crisp inputs, x_1 and y_1 *(project funding* and *project staffing),* and determine the degree to which these inputs belong to each of the appropriate fuzzy sets. The crisp input is always a numerical value limited to the universe of discourse. In our case, values of x_1 and y_1 are limited to the universe of discourses *X* and *Y*, respectively. The ranges of the universe of discourses can be determined by expert judgements. For instance, if we need to examine the risk involved in developing the 'fuzzy' project, we can ask the expert to give numbers between 0 and l00 per cent that represent the project funding and the project staffing, respectively. In other words, the expert is required to answer to what extent the project funding and the project staffing are really adequate. Of course, various fuzzy systems use a variety of different crisp inputs. While some of the inputs can be measured directly (height, weight, speed, distance, temperature, pressure etc.), some of them can be based only on expert estimate.

Once the crisp inputs, x_1 and y_1, are obtained, they are fuzzified against the appropriate linguistic fuzzy sets. The crisp input *x*l (project funding rated by the expert as 35 per cent) corresponds to the membership functions *A*1 and A2 *(inadequate* and *marginal)* to the degrees of 0.5 and 0.2, respectively, and the crisp input y_1 (project staffing rated as 60 per cent) maps the membership functions B1 and B2 *(small* and *large)* to the degrees of 0.1 and 0.7, respectively. In this manner, each input is fuzzified over all the membership functions used by the fuzzy rules.

Step 2: ***Rule evaluation***

The second step is to take the fuzzified inputs, $\mu(_{x=A1}) = 0.5$, $\mu(_{x=A2}) = 0.2$, $\mu(_{y=B1}) = 0.1$ and $\mu(_{y=B2}) = 0.7$, and apply them to the antecedents of the fuzzy rules. If a given fuzzy rule has multiple antecedents, the fuzzy operator (AND or OR) is used to obtain a single number that represents the result of the antecedent evaluation. This number (the truth value) is then applied to the consequent membership function.

To evaluate the disjunction of the rule antecedents, we use the OR fuzzy operation. Typically, fuzzy expert systems make use of the classical fuzzy operation *union* shown in Figure 3.10 (Rule 1):

$$\mu_{AUB}(x) = max\ [\mu_A(x), \mu_B(x)]$$

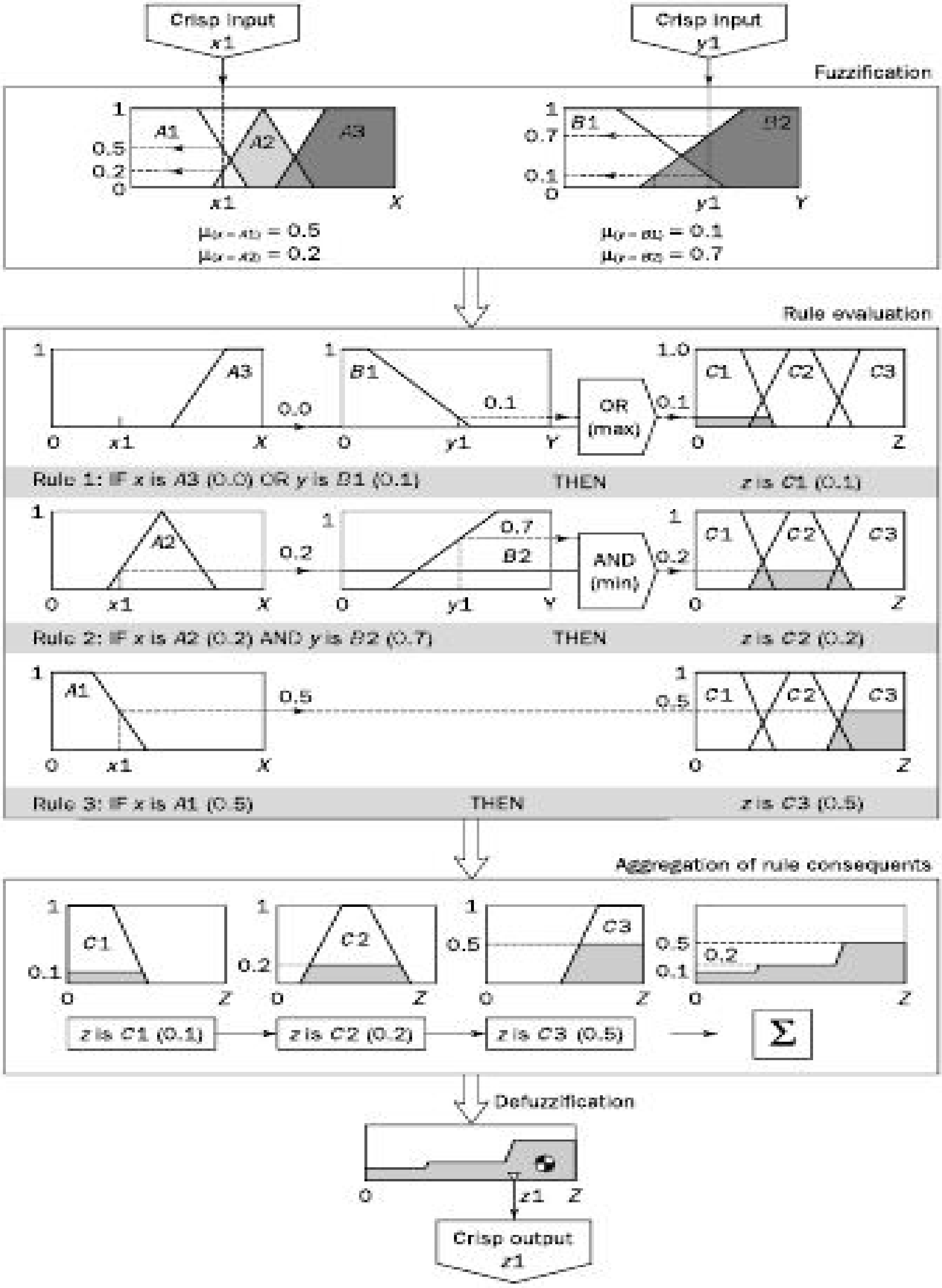


Figure 3.10. The basic structure of Mamdani-style fuzzy inference

However, the OR operation can be easily customised if necessary. For example, the MATLAB Fuzzy Logic Toolbox has two built-in OR methods: *max* and the probabilistic OR method, *probor.* The probabilistic OR, also known as the algebraic sum, is calculated as:

$$\mu_{A \cup B}(x) = probor\ [\mu_A(x), \mu_B(x)] = \mu_A(x) + \mu_B(x) - \mu_A(x) \times \mu_B(x)$$

Similarly, in order to evaluate the conjunction of the rule antecedents, we apply the AND fuzzy operation *intersection* also has shown in Figure 3.10 (Rule 2):

$$\mu_{A \cap B}(x) = \min [\mu_A(x), \mu_B(x)]$$

The Fuzzy Logic Toolbox also supports two AND methods: *min* and the product, *prod.* The product is calculated as:

$$\mu_{A \cap B}(x) = prod\ [\mu_A(x), \mu_B(x)] = \mu_A(x) \times \mu_B(x)$$

Fuzzy researchers have proposed and applied several approaches to execute AND and OR fuzzy operators (Cox, 1999) and, of course, different methods may lead to different results. Most fuzzy packages also allow us to customise the AND and OR fuzzy operations and a user is required to make the choice.

Rule: 1

IF *x* is *A*3 (0.0)
OR *y* is B1 (0.1)
THEN *z* is C1 (0.1)

$$\mu_{C1}(z) = max\ [\mu_{A3}(x), \mu_{B1}(y)] = max\ [0.0,0.1] = 0.1$$

or

$$\mu_{C1}(z) = probor\ [\mu_{A3}(x), \mu_{B1}(y)] = 0.0 + 0.1 - 0.0 \times 0.1 = 0.1$$

Rule: 2

IF *x* is *A*2 (0.2)
AND *y* is B2 (0.7)
THEN z is C2 (0.2)

$$\mu_{C2}(z) = min\ [\mu_{A2}(x), \mu_{B2}(y)] = min\ [0.2,0.7] = 0.2$$

or

$$\mu_{C2}(z) = prod\ [\mu_{A2}(x), \mu_{B2}(y)] = 0.2 \times 0.7 = 0.14$$

Thus, Rule 2 can be also represented as shown in Figure 3.11.

Now the result of the antecedent evaluation can be applied to the membership function of the consequent. In other words, the consequent membership function is clipped or scaled to the level of the truth value of the rule antecedent.

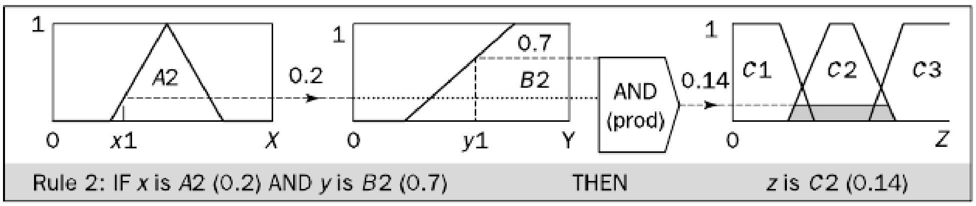


Figure 3.11. The AND *product* fuzzy operation

The most common method of correlating the rule consequent with the truth value of the rule antecedent is to simply cut the consequent membership function at the level of the antecedent truth. This method is called clipping or correlation minimum. Since the top of the membership function is sliced, the clipped fuzzy set loses some information. However, clipping is still often preferred because it involves less complex and faster mathematics, and generates an aggregated output surface that is easier to defuzzify.

While clipping is a frequently used method, scaling or correlation product offers a better approach for preserving the original shape of the fuzzy set. The original membership function of the rule consequent is adjusted by multiplying all its membership degrees by the truth value of the rule antecedent. This method, which generally loses less information, can be very useful in fuzzy expert systems.

Clipped and scaled membership functions are illustrated in Figure 3.12.

Step 3: ***Aggregation of the rule outputs***

Aggregation is the process of unification of the outputs of all rules. In other words, we take the membership functions of all rule consequents previously clipped or scaled and combine them into a single fuzzy set. Thus, the input of the aggregation process is the list of clipped or scaled consequent membership functions, and the output is one fuzzy set for each output variable. Figure 3.10 shows how the output of each rule is aggregated into a single fuzzy set for the overall fuzzy output.

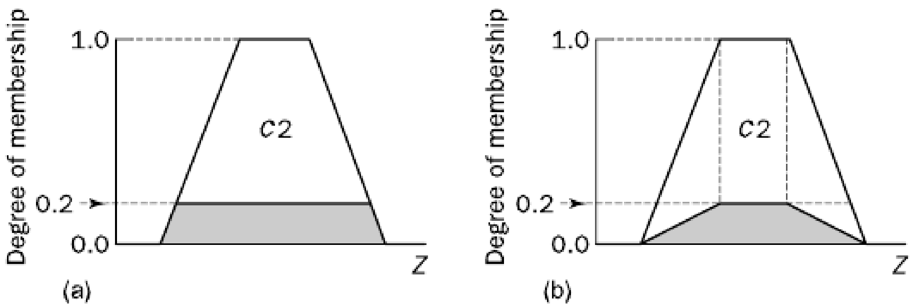


Figure 3.12. Clipped (a) and scaled (b) membership functions

Step 4: ***Defuzzification***

The last step in the fuzzy inference process is defuzzification. Fuzziness helps us to evaluate the rules, but the final output of a fuzzy system has to be a crisp number.

The input for the defuzzification process is the aggregate output fuzzy set and the output is a single number.

There are several defuzzification methods (Cox, 1999), but probably the most popular one is the centroid technique. It finds the point where a vertical line would slice the aggregate set into two equal masses. Mathematically this centre of gravity (COG) can be expressed as

$$COG = \frac{\int_a^b \mu_A(x)x\,dx}{\int_a^b \mu_A(x)\,dx}$$

As Figure 3.13 shows, a centroid defuzzification method finds a point representing the centre of gravity of the fuzzy set, *A*, on the interval, *ab*.

In theory, the COG is calculated over a continuum of points in the aggregate output membership function, but in practice, a reasonable estimate can be obtained by calculating it over a sample of points, as shown in Figure 3.13. In this case, the following formula is applied:

$$\mathrm{COG} = \frac{\sum_{x=a}^{b} \mu_\mathrm{A}(\mathrm{x})\mathrm{x}}{\sum_{x=a}^{b} \mu_\mathrm{A}(\mathrm{x})}$$

Let us now calculate the centre of gravity for this problem. The solution is presented in Figure 3.14.

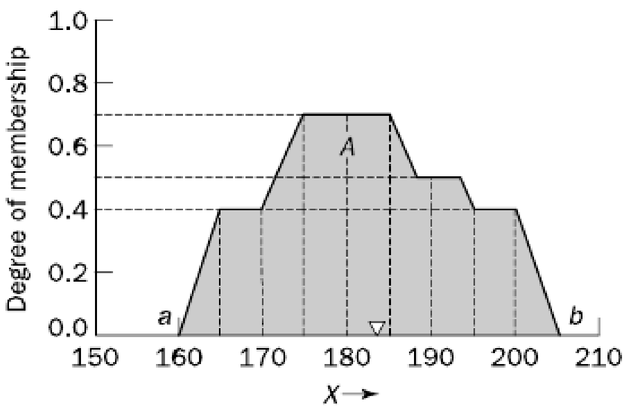


Figure 3.13. The centroid method of defuzzification

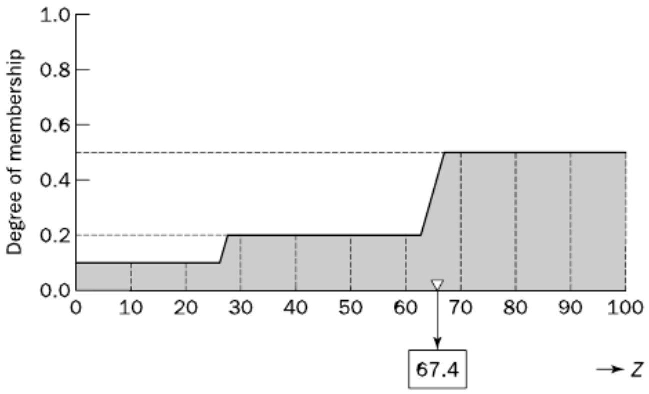


Figure 3.14. Defuzzifying the solution variable's fuzzy set

$$COG = \frac{(0+10+20)\times 0.1 + (30+40+50+60)\times 0.2 + (70+80+90+100)\times 0.5}{0.1+0.1+0.1+0.2+0.2+0.2+0.2+0.5+0.5+0.5+0.5} = 67.4$$

Thus, the result of defuzzification, crisp output z1, is 67.4. It means, for instance, that the risk involved in our 'fuzzy' project is 67.4 percent.

3.2.6.2 Sugeno-style inference

Mamdani-style inference, requires us to find the centroid of a two-dimensional shape by integrating across a continuously varying function. In general, this process is not computationally efficient.

Sugeno-style inference method was first introduced by Michio Sugeno, the 'Zadeh of Japan', in 1985 (Sugeno, 1985). A singleton, or more precisely a fuzzy singleton, is a fuzzy set with a membership function that is unity at a single particular point on the universe of discourse and zero everywhere else.

Sugeno-style fuzzy inference is very similar to the Mamdani method. Sugeno changed only a rule consequent. Instead of a fuzzy set, he used a mathematical function of the input variable. The format of the Sugeno-style fuzzy rule is

IF x is A
AND y is B
THEN z is $f(x, y)$

where x, y and z are linguistic variables; A and B are fuzzy sets on universe of discourses X and Y, respectively; and $f(x,$y) is a mathematical function.

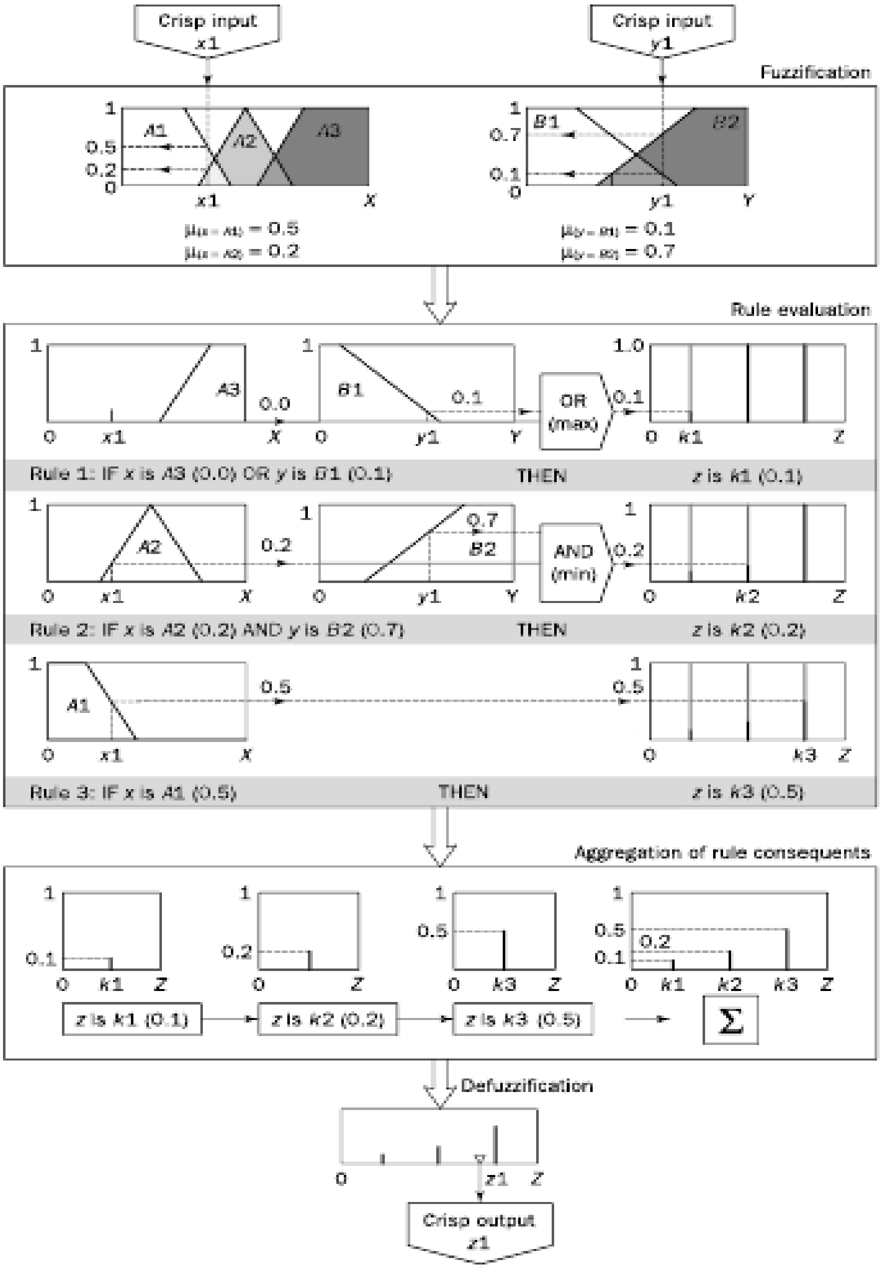


Figure 3.15. The basic structure of Sugeno-style fuzzy inference

The most commonly used zero-order Sugeno fuzzy model applies fuzzy rules in the following form:

IF	*x* is *A*
AND	*y* is *B*
THEN	*z* is *k*

where *k* is a constant.

In this case, the output of each fuzzy rule is constant. In other words, all consequent membership functions are represented by singleton spikes. Figure 3.15

shows the fuzzy inference process for a zero-order Sugeno model. Let us compare Figure 3.15 with Figure 3.10. The similarity of Sugeno and Mamdani methods is quite noticeable. The only distinction is that rule consequents are singletons in Sugeno's method.

As we can see from Figure 3.15, the aggregation operation simply includes all the singletons. Now we can find the weighted average (WA) of these singletons:

$$WA = \frac{\mu(k1) \times k1 + \mu(k2) \times k2 + \mu(k3) \times k3}{\mu(k1) + \mu(k2) + \mu(k3)} = \frac{0.1 \times 20 + 0.2 \times 50 + 0.5 \times 80}{0.1 + 0.2 + 0.5}$$
$$= 65$$

Thus, a zero-order Sugeno system might be sufficient for our problem's needs. Fortunately, singleton output functions satisfy the requirements of a given problem quite often.

The Mamdani method is widely accepted for capturing expert knowledge. It allows us to describe the expertise in more intuitive, more human-like manner. However, Mamdani-type fuzzy inference entails a substantial computational burden. On the other hand, the Sugeno method is computationally effective and works well with optimization and adaptive techniques, which makes it very attractive in control problems, particularly for dynamic nonlinear systems (Negnevitsky, 2005).

3.2.7. Building a fuzzy expert system

To illustrate the design of a fuzzy expert system, we will consider a problem of operating a service centre of spare parts (Turksen *et al.,* 1992).

A service centre keeps spare parts and repairs failed ones. A customer brings a failed item and receives a spare of the same type. Failed parts are repaired, placed on the shelf, and thus become spares. If the required spare is available on the shelf, the customer takes it and leaves the service centre. However, if there is no spare on the shelf, the customer has to wait until the needed item becomes available. The objective here is to advise a manager of the service centre on certain decision policies to keep the customers satisfied.

A typical process in developing the fuzzy expert system incorporates the following steps:

1. Specify the problem and define linguistic variables.
2. Determine fuzzy sets.
3. Elicit and construct fuzzy rules.
4. Encode the fuzzy sets, fuzzy rules and procedures to perform fuzzy inference into the expert system.
5. Evaluate and tune the system.

Step 1: ***Specify the problem and define linguistic variables***

The first, and probably the most important, step in building any expert system is to specify the problem. We need to describe our problem in terms of knowledge engineering. In other words, we need to determine problem input and output variables and their ranges.

For our problem, there are four main linguistic variables: average waiting time (mean delay) *m,* repair utilisation factor of the service centre p, number of servers s, and initial number of spare parts *n.*

The customer's average waiting time, m, is the most important criterion of the service centre's performance. The actual mean delay in service should not exceed the limits acceptable to customers.

The repair utilisation factor of the service centre, p, is the ratio of the customer arrival rate, A, to the customer departure rate, p. Magnitudes of A and p indicate the rates of an item's failure (failures per unit time) and repair (repairs per unit time), respectively. Apparently, the repair rate is proportional to the number of servers, *s*. To increase the productivity of the service centre, its manager will try to keep the repair utilisation factor as high as possible.

The number of servers, *s*, and the initial number of spares, *n*, directly affect the customer's average waiting time, and thus have a major impact on the centre's performance. By increasing *s* and n, we achieve lower values of the mean delay, but, at the same time we increase the costs of employing new servers, building up the number of spares and expanding the inventory capacities of the service centre for additional spares.

Let us determine the initial number of spares *n*, given the customer's mean delay *m*, number of servers *s*, and repair utilisation factor, p. Thus, in the decision model considered here, we have three inputs - m, *s* and p, and one output - n. In other words, a manager of the service centre wants to determine the number of spares required to maintain the actual mean delay in customer service within an acceptable range.

Now we need to specify the ranges of our linguistic variables. Suppose we obtain the results shown in Table 3.5 where the intervals for m, *s* and *n* are normalised to be within the range of [0,1] by dividing base numerical values by the corresponding maximum magnitudes.

Table 3.5. Linguistic variables and their ranges

Linguistic variable: Mean delay, m		
Linguistic value	**Notation**	**Numerical range (normalised)**
Very Short	VS	[0, 0.3]
Short	S	[0.1, 0.5]
Medium	M	[0.4, 0.7]
Linguistic variable: Number of servers, s		
Linguistic value	**Notation**	**Numerical range (normalised)**
Small	S	[0, 0.35]
Medium	M	[0.30, 0.70]
Large	L	[0.60, 1]
Linguistic variable: Repair utilisation factor, p		
Linguistic value	**Notation**	**Numerical range**
Low	L	[0, 0.6]
Medium	M	[0.4, 0.8]
High	H	[0.6, 1]
Linguistic variable: Number of spares, n		
Linguistic value	**Notation**	**Numerical range (normalised)**
Very Small	VS	[0, 0.30]
Small	S	[0, 0.40]
Rather Small	RS	[0.25, 0.45]
Medium	M	[0.30, 0.70]
Rather Large	RL	[0.55, 0.75]
Large	L	[0.60, 1]
Very Large	VL	[0.70, 1]

For the customer mean delay *m,* we consider only three linguistic values - *Very Short, Short* and *Medium* because other values such as *Long* and *Very Long* are simply not practical. A manager of the service centre cannot afford to keep customers waiting longer than a medium time.

In practice, all linguistic variables, linguistic values and their ranges are usually chosen by the domain expert.

Step 2: ***Determine fuzzy sets***

Fuzzy sets can have a variety of shapes. However, a triangle or a trapezoid can often provide an adequate representation of the expert knowledge, and at the same time significantly simplifies the process of computation.

Figures 3.16 to 3.19 show the fuzzy sets for all linguistic variables used in our problem. As you may notice, one of the key points here is to maintain sufficient overlap in adjacent fuzzy sets for the fuzzy system to respond smoothly.

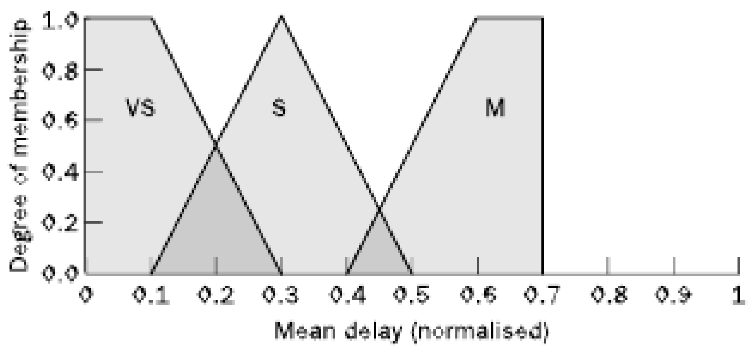


Figure 3.16. Fuzzy sets of mean delay m

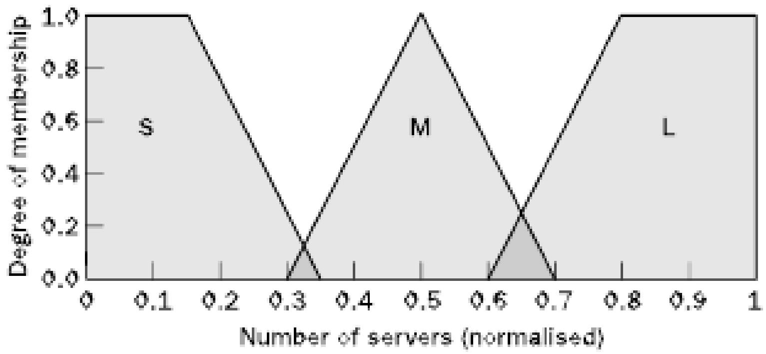


Figure 3.17. Fuzzy sets of number of servers s

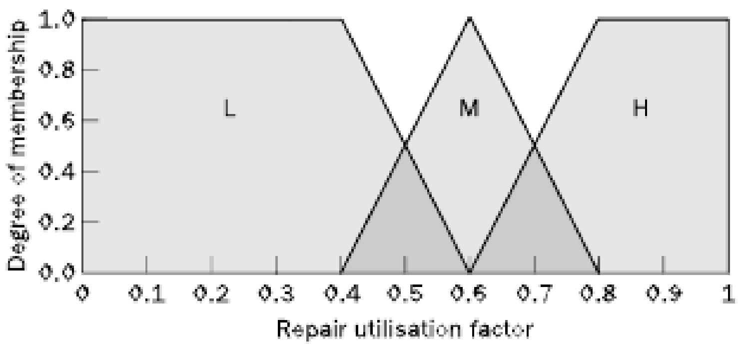


Figure 3.18. Fuzzy sets of repair utilization factor p

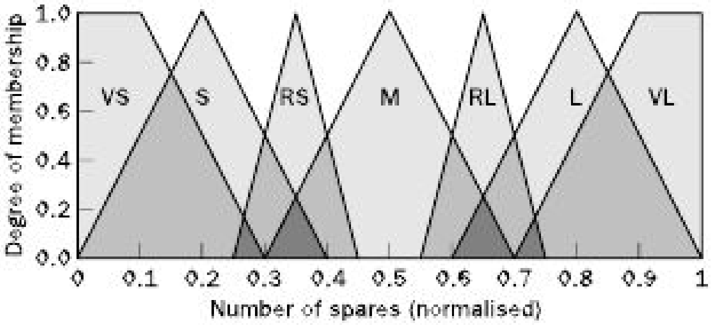


Figure 3.19. Fuzzy sets of number of spares n

Step 3: **Elicit and construct fuzzy rules**

Next we need to obtain fuzzy rules. To accomplish this task, we might ask the expert to describe how the problem can be solved using the fuzzy linguistic variables defined previously.

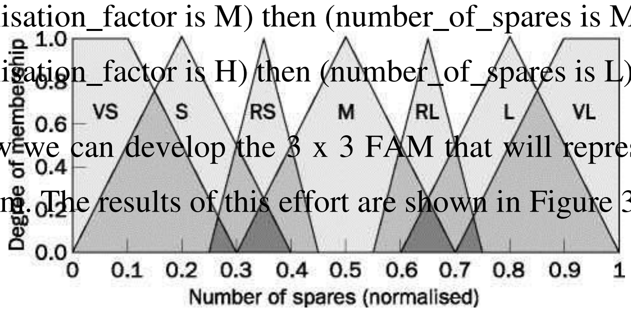
Required knowledge also can be collected from other sources such as books, computer databases, flow diagrams and observed human behaviour. In our case, we could apply rules provided in the research paper (Turksen *etal.,* 1992).

There are three input and one output variables in our example. It is often convenient to represent fuzzy rules in a matrix form. A two-by-one system (two inputs and one output) is depicted as an M x N matrix of input variables. The linguistic values of one input variable form the horizontal axis and the linguistic values of the other input variable form the vertical axis. At the intersection of a row and a column lies the linguistic value of the output variable. For a three-by-one system (three inputs and one output), the representation takes the shape of an M x N x K cube. This form of representation is called a fuzzy associative memory (FAM).

Let us first make use of a very basic relation between the repair utilization factor p, and the number of spares *n,* assuming that other input variables are fixed. This relation can be expressed in the following form: if p increases, then *n* will not decrease. Thus we could write the following three rules:

1. If (utilisation_factor is L) then (number_of_spares is S)
2. If (utilisation_factor is M) then (number_of_spares is M)
3. If (utilisation_factor is H) then (number_of_spares is L)

Now we can develop the 3 x 3 FAM that will represent the rest of the rules in a matrix form. The results of this effort are shown in Figure 3.20.



Meanwhile, a detailed analysis of the service centre operation, together with an 'expert touch' (Turksen *et al.,* 1992), may enable us to derive 27 rules that represent complex relationships between all variables used in the expert system. Table 3.6 contains these rules and Figure 3.21 shows the cube (3 x 3 x 3) FAM representation.

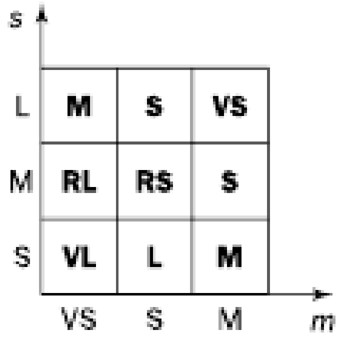


Figure 3.20. The square FAM representation

Table 3.6. The rule table

Rule	m	s	p	n	Rule	m	s	p	n	Rule	m	s	p	n
1	VS	S	L	VS	10	VS	S	M	S	19	VS	S	H	VL
2	S	S	L	VS	11	S	S	M	VS	20	S	S	H	L
3	M	S	L	VS	12	M	S	M	VS	21	M	S	H	M
4	VS	M	L	VS	13	VS	M	M	RS	22	VS	M	H	M
5	S	M	L	VS	14	S	M	M	S	23	S	M	H	M
6	M	M	L	VS	15	M	M	M	VS	24	M	M	H	S
7	VS	L	L	S	16	VS	L	M	M	25	VS	L	H	RL
8	S	L	L	S	17	S	L	M	RS	26	S	L	H	M
9	M	L	L	VS	18	M	L	M	S	27	M	L	H	RS

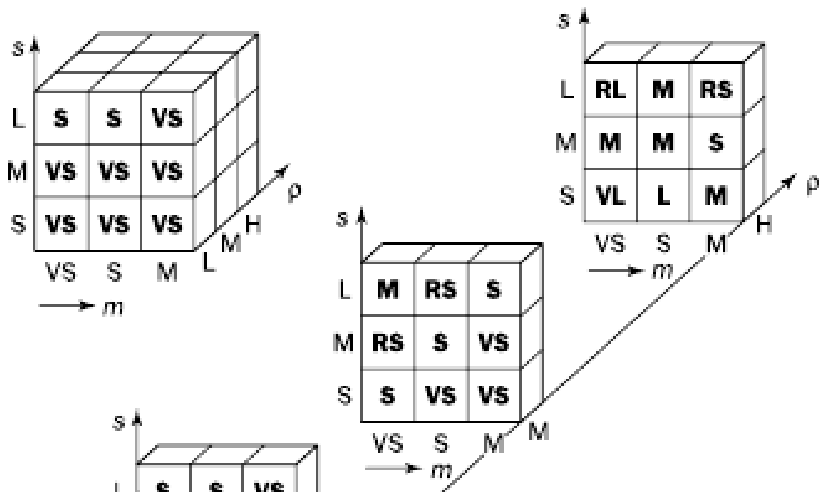


Figure 3.21. Cube FAM and sliced cube FAM representations

First we developed 12 (3 + 3 x 3) rules, but then we obtained 27 (3 x 3 x 3) rules. If we implement both schemes, we can compare results; only the system's performance can tell us which scheme is better.

Rule Base 1

1. If (utilisation_factor is L) then (number_of_spares is S)
2. If (utilisation_factor is M) then (number_of_spares is M)
3. If (utilisation_factor is H) then (number_of_spares is L)
4. If (mean_delay is VS) and (number_of_servers is S) then (number_of_spares is VL)
5. If (mean_delay is S) and (number_of_servers is S) then (number_of_spares is L)
6. If (mean_delay is M) and (number_of_servers is S) then (number_of_spares is M)
7. If (mean_delay is VS) and (number_of_servers is M) then (number_of_spares is RL)
8. If (mean_delay is S) and (number_of_servers is M) then (number_of_spares is RS)
9. If (mean_delay is M) and (number_of_servers is M) then (number_of_spares is S)
10. If (mean_delay is VS) and (number_of_servers is L) then (number_of_spares is M)
11. If (mean_delay is S) and (number_of_servers is L) then (number_of_spares is S)
12. If (mean_delay is M) and (number_of_servers is L) then (number_of_spares is VS)

Rule Base 2

1. If (mean_delay is VS) and (number_of_servers is S) and (utilisation_factor is L) then (number_of_spares is VS)
2. If (mean_delay is S) and (number_of_servers is S) and (utilisation_factor is L) then (number_of_spares is VS)
3. If (mean_delay is M) and (number_of_servers is S) and

(utilisation_factor is L) then (number_of_spares is VS)

4. If (mean_delay is VS) and (number_of_servers is M) and (utilisation_factor is L) then (number_of_spares is VS)

5. If (mean_delay is S) and (number_of_servers is M) and (utilisation_factor is L) then (number_of_spares is VS)

6. If (mean_delay is M) and (number_of_servers is M) and (utilisation_factor is L) then (number_of_spares is VS)

7. If (mean_delay is VS) and (number_of_servers is L) and (utilisation_factor is L) then (number_of_spares is S)

8. If (mean_delay is S) and (number_of_servers is L) and (utilisation_factor is L) then (number_of_spares is S)

9. If (mean_delay is M) and (number_of_servers is L) and (utilisation_factor is L) then (number_of_spares is VS)

10. If (mean_delay is VS) and (number_of_servers is S) and (utilisation_factor is M) then (number_of_spares is S)

11. If (mean_delay is S) and (number_of_servers is S) and (utilisation_factor is M) then (number_of_spares is VS)

12. If (mean_delay is M) and (number_of_servers is S) and (utilisation_factor is M) then (number_of_spares is VS)

13. If (mean_delay is VS) and (number_of_servers is M) and (utilisation_factor is M) then (number_of_spares is RS)

14. If (mean_delay is S) and (number_of_servers is M) and (utilisation_factor is M) then (number_of_spares is S)

15. If (mean_delay is M) and (number_of_servers is M) and (utilisation_factor is M) then (number_of_spares is VS)

16. If (mean_delay is VS) and (number_of_servers is L) and (utilisation_factor is M) then (number_of_spares is M)

17. If (mean_delay is S) and (number_of_servers is L) and (utilisation_factor is M) then (number_of_spares is RS)

18. If (mean_delay is M) and (number_of_servers is L) and (utilisation_factor is M) then (number_of_spares is S)

19. If (mean_delay is VS) and (number_of_servers is S) and (utilisation_factor is H) then (number_of_spares is VL)

20. If (mean_delay is S) and (number_of_servers is S) and (utilisation_factor is H) then (number_of_spares is L)

21. If (mean_delay is M) and (number_of_servers is S) and (utilisation_factor is H) then (number_of_spares is M)

22. If (mean_delay is VS) and (number_of_servers is M) and (utilisation_factor is H) then (number_of_spares is M)

23. If (mean_delay is S) and (number_of_servers is M) and (utilisation_factor is H) then (number_of_spares is M)

24. If (mean_delay is M) and (number_of_servers is M) and (utilisation_factor is H) then (number_of_spares is S)

25. If (mean_delay is VS) and (number_of_servers is L) and (utilisation_factor is H) then (number_of_spares is RL)

26. If (mean_delay is S) and (number_of_servers is L) and (utilisation_factor is H) then (number_of_spares is M)

27. If (mean_delay is M) and (number_of_servers is L) and (utilisation_factor is H) then (number_of_spares is RS)

Step 4: ***Encode the fuzzy sets, fuzzy rules and procedures to perform fuzzy inference into the expert system***

The next task after defining fuzzy sets and fuzzy rules is to encode them, and thus actually build a fuzzy expert system. To accomplish this task, we may choose one of two options: to build our system using a programming language such as C or Pascal, or to apply a fuzzy logic development tool such as MATLAB Fuzzy Logic Toolbox® from the MathWorks or Fuzzy Knowledge Builder™ from Fuzzy Systems Engineering.

Most experienced fuzzy system builders often prefer the C/C++ programming language (Cox, 1999; Li and Gupta, 1995) because it offers greater flexibility. However, for rapid developing and prototyping a fuzzy expert system, the best choice is a fuzzy logic development tool. Such a tool usually provides complete environments for building and testing fuzzy systems. For example, the MATLAB Fuzzy Logic Toolbox has five integrated graphical editors: the fuzzy inference system editor, the rule editor, the membership function editor, the fuzzy inference viewer, and the output surface viewer. All these features make designing fuzzy systems much easier. This option is also preferable for novices, who do not have sufficient experience in building fuzzy expert systems. When a fuzzy logic development tool is chosen, the knowledge engineer needs only to encode fuzzy rules in English- like syntax, and define membership functions graphically.

To build our fuzzy expert system, we will use one of the most popular tools, the MATLAB Fuzzy Logic Toolbox. It provides a systematic framework for computing with fuzzy rules and graphical user interfaces. It is easy to master and convenient to use, even for new fuzzy system builders.

Step 5: ***Evaluate and tune the system***

The last, and the most laborious, task is to evaluate and tune the system. We want to see whether our fuzzy system meets the requirements

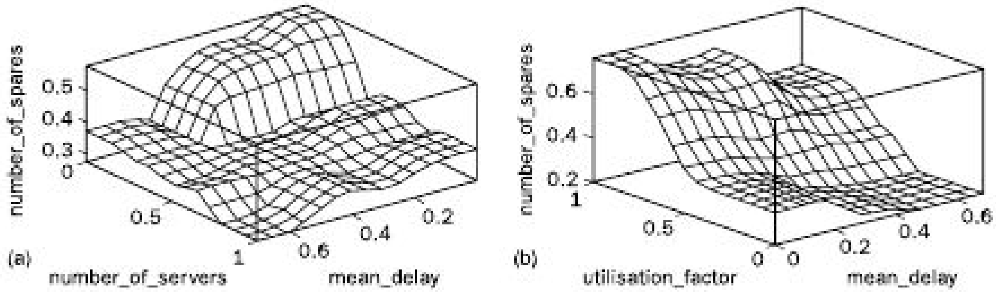


Figure 3.22. Three-dimensional plots for rule base 1

specified at the beginning. Several test situations depend on the mean delay, number of servers and repair utilization factor. The Fuzzy Logic Toolbox can generate surface to help us analyze the system's performance. Figure 3.22 represents three-dimensional plots for the two-input one-output system.

The Fuzzy Logic Toolbox has a special capability: it can generate a three-dimensional output surface by varying any two of the inputs and keeping other inputs constant. Thus we can observe the performance of our three-input one-output system on two three-dimensional plots.

Although the fuzzy system works well, we may attempt to improve it by applying Rule Base 2. The results are shown in Figure 3.23. If we compare Figures 3.22 and 3.23, we will see the improvement.

However, even now, the expert might not be satisfied with the system performance. To improve it, he or she may suggest additional sets - *Rather Small* and *Rather Large* - on the universe of discourse *Number of servers* (as shown in Figure 3.24), and to extend the rule base according to the FAM presented in Figure 3.25. The ease with which a fuzzy system can be modified and extended permits us to follow the expert suggestions and quickly obtain results shown in Figure 3.26.

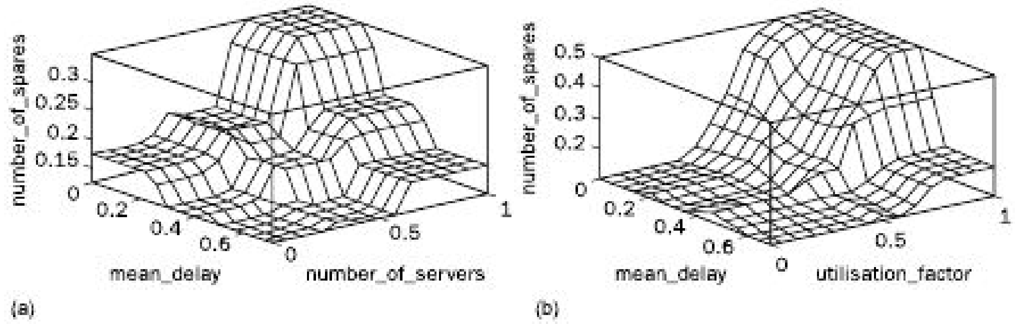


Figure 3.23. Three dimensional plots for rule base 2

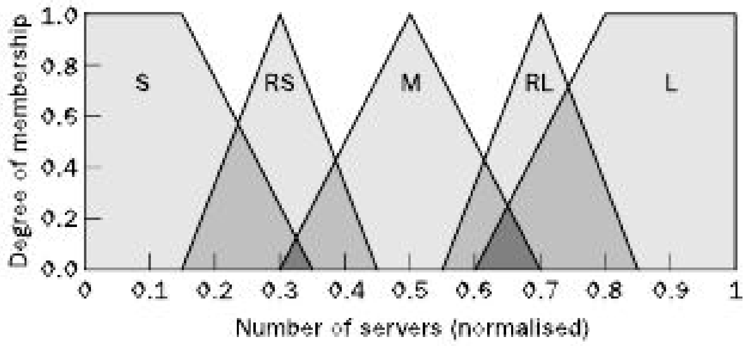


Figure 3.24. Modified fuzzy sets of number of servers s

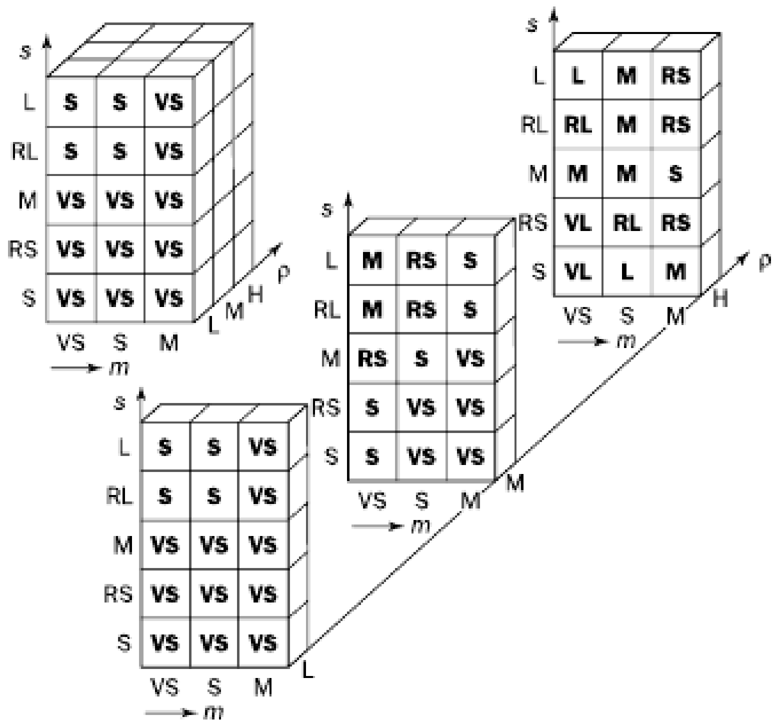


Figure 3.25. Cube FAM of rule base 3

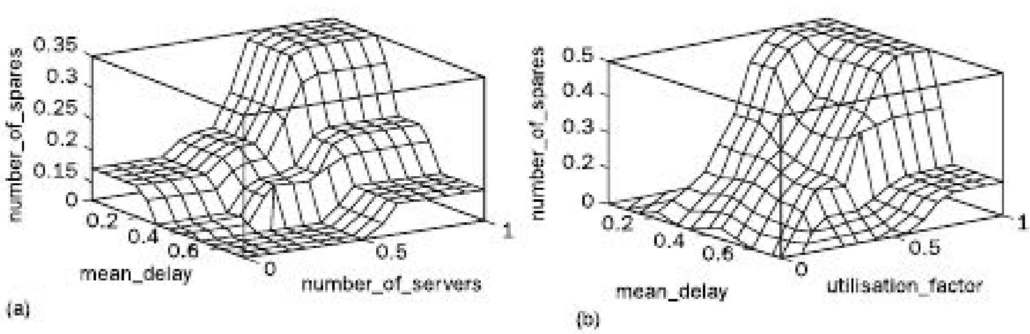


Figure 3.26. Three dimensional plots for rule base 3

In general, tuning a fuzzy expert system takes much more time and effort than determining fuzzy sets and constructing fuzzy rules. Usually a reasonable solution to the problem can be achieved from the first series of fuzzy sets and fuzzy rules. This is an acknowledged advantage of fuzzy logic; however, improving the system becomes rather an art than engineering. Tuning fuzzy systems may involve executing a number of actions in the following order:

1 Review model input and output variables, and if required redefine their ranges. Pay particular attention to the variable units. Variables used in the same domain must be measured in the same units on the universe of discourse.

2 Review the fuzzy sets, and if required define additional sets on the universe of discourse. The use of wide fuzzy sets may cause the fuzzy system to perform roughly.

3 Provide sufficient overlap between neighbouring sets. Although there is no precise method to determine the optimum amount of overlap, it is suggested that triangle-to-triangle and trapezoid-to-triangle fuzzy sets should overlap between 25 and 50 per cent of their bases (Cox, 1999).

4 Review the existing rules, and if required add new rules to the rule base.

5 Examine the rule base for opportunities to write hedge rules to capture the pathological behaviour of the system.

6 Adjust the rule execution weights. Most fuzzy logic tools allow control of the importance of rules by changing a weight multiplier. In the Fuzzy Logic Toolbox, all rules have a default weight of (1.0), but the user can reduce the force of any rule by adjusting its weight. For example, if we specify

If (utilisation_factor is H) then (number_of_spares is L) (0.6)

then the rule's force will be reduced by 40 percent.

7 Revise shapes of the fuzzy sets. In most cases, fuzzy systems are highly tolerant of a shape approximation, and thus a system can still behave well even when the shapes of the fuzzy sets are not precisely defined.

The centroid technique appears to provide consistent results. This is a well-balanced method sensitive to the height and width of the total fuzzy region as well as to sparse singletons. Therefore, unless you have a strong reason to believe that your fuzzy system will behave better under other defuzzification methods, the centroid technique is recommended (Negnevitsky, 2005).

3.2.8. Performance criteria

The estimated performance was calculated with Mean Percentage Error (MPE), Mean Absolute Percentage Error (MAPE), Determination coefficient (R^2), Root Mean Squared Error (RMSE). The results of FES predicted LBW were compared with the actual weighed values (Taşdemir, et al, 2010).

a) Mean Percentage Error

$$MPE = \frac{\sum_{i=1}^{n} \frac{Y_i - Y_i}{Y_i}}{n} \times 100\%$$

b) Mean Absolute Percentage Error

$$MAPE = \frac{\sum_{i=1}^{n} \left| \frac{Y_i - Y_i}{Y_i} \right|}{n} \times 100\%$$

c) Determination coefficient

$$R^2 = \frac{\sum_{i=1}^{n} \left(Y_i - \overline{Y} \right)^2}{\sum_{i=1}^{n} \left(Y_i - \overline{Y} \right)^2}$$

d) Root Mean Squared Error

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} \left(Y_i - \overline{Y} \right)^2}{n}}$$

Where,

Y_i – observed value,

$\widehat{Y_i}$ – predicted value,

$\overline{Y}$ – Arithmetic mean,

n – the total number of observations.

.

4. RESULTS AND DISCUSSIONS

4.1. FES Design For Live Body Weight Prediction

Descriptive statistics concerning body measurements and live body weight of hair goats grown in Siirt are shown in Table 4.1. Correlation coefficients between body measurements and live body weight are shown in Table 4.2.

Tablo 4.1. Descriptive statistics of the obtained data

Morphological Traits	N	Mean ± S	Minimum	Maximum
Heart Girth (cm)	81	85.84 ± 5.605	74	96
Body Depth (cm)	81	88.43 ± 7.586	73	105
Body Length (cm)	81	67.64 ± 4.293	56	82
Live Body Weight (kg)	81	39.16 ± 7.131	22.40	56.60

Tablo 4.2. Correlation coefficients between body measurements and live body weight

	LBW	HG	BD
HG	0.852**		
BD	0.767**	0.764**	
BL	0.776**	0.744**	0.650**

**: p<0.01

The general structure of the developed FES is shown in Figure 4.1.

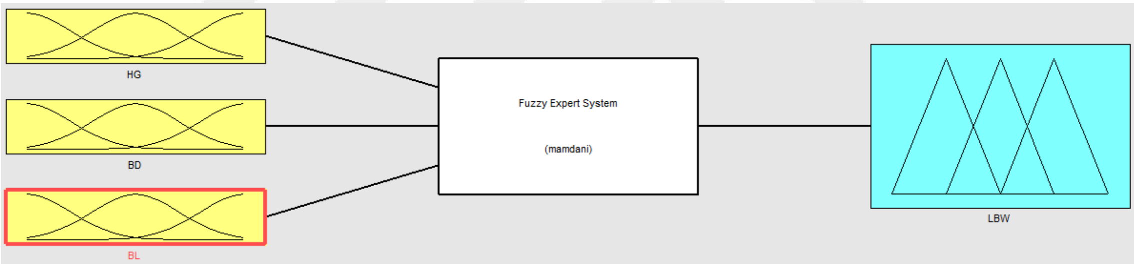


Figure 4.1. Structure of the developed FES

Plots representing the relations between inputs and output were shown in Figure 4.2-4.4.

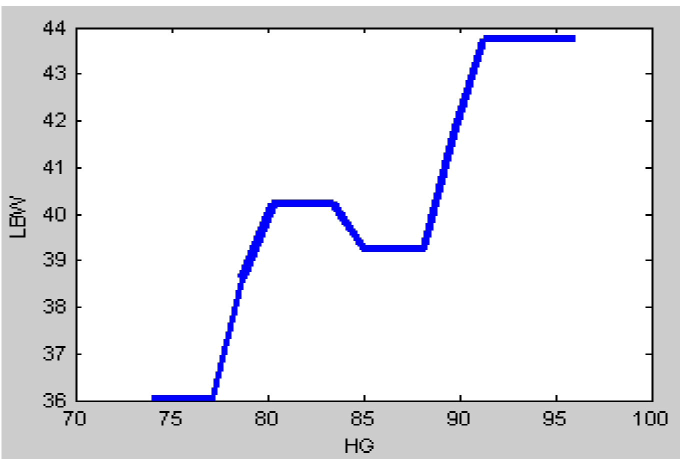


Figure 4.2. Relation between HG and LBW

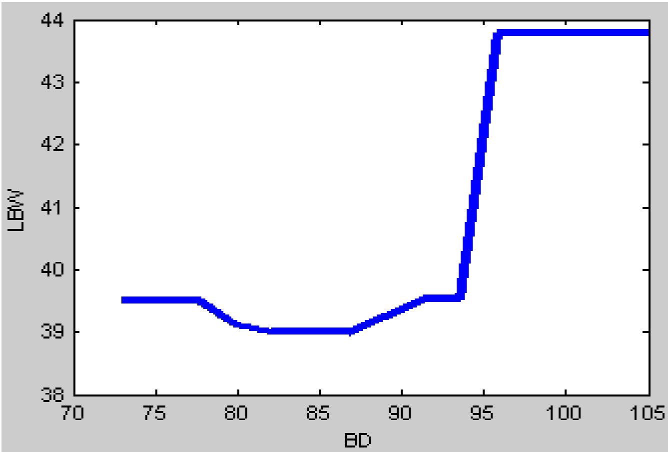


Figure 4.3. Relation between BD and LBW

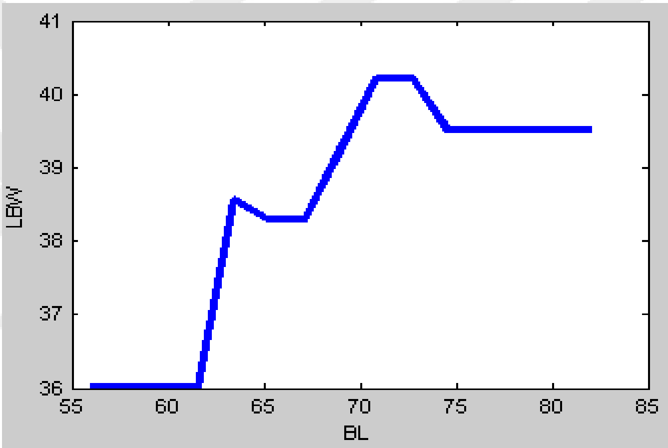


Figure 4.4. Relation between BL and LBW

Three dimension graphics explaining the FES were shown in the Figure 4.5-4.7

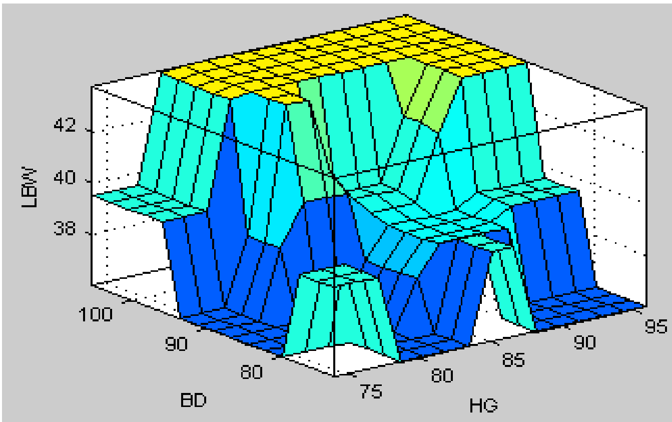


Figure 4.5. 3D representation of LBW by BD and HG

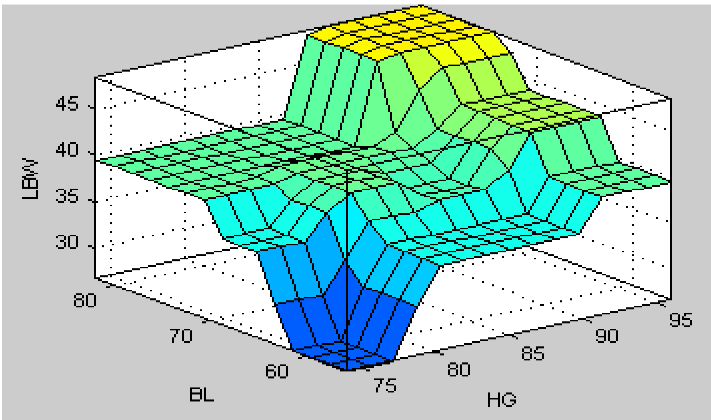


Figure 4.6. 3D representation of LBW by BL and HG

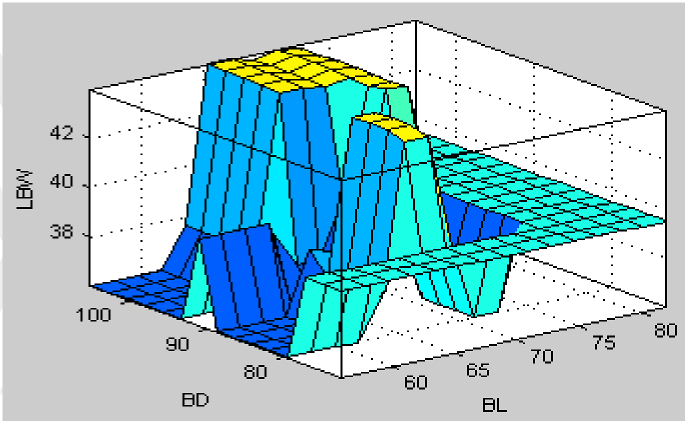


Figure 4.7. 3D representation of LBW by BD and BL

4.2. Fuzzification

Input and output crisp numerical data were fuzzified and converted into linguistic variables (Table 4.3).

Table 4.3. Linguistic terms used for the body measurements

HG range (cm)	Linguistic terms	Membership functions
74 – 80	Short	trapezoidal
78 – 85	Medium	triangular
83 – 90	Long	triangular
88 – 96	Very Long	trapezoidal
BD range (cm)	Linguistic terms	Membership functions
73 – 80	Short	trapezoidal
78 – 90	Medium	triangular
88 – 95	Long	triangular
93 – 105	Very Long	trapezoidal
BL range (cm)	Linguistic terms	Membership functions
56 – 65	Short	trapezoidal
63 – 70	Medium	triangular
68 – 74	Long	triangular
72 – 82	Very Long	trapezoidal

LBW range (kg)	Linguistic terms	Membership functions
22 – 32	Low	trapezoidal
30 – 42	Medium	triangular
39 – 48	High	triangular
45 – 57	Very High	trapezoidal

It was set up triangular and trapezoid membership functions for the fuzzy variables as inputs and output. The fuzzy sets and membership functions for each of the 3 input variables and 1 output variable were determined (Figure 4.8-4.11).

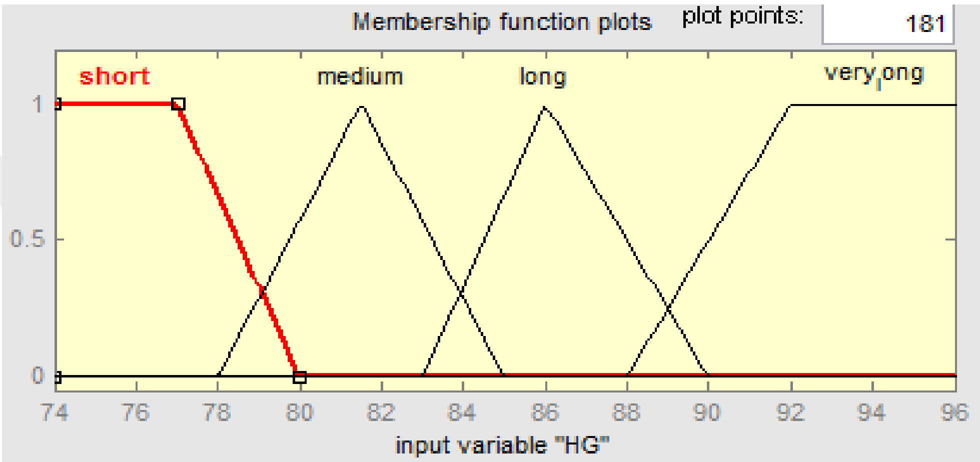


Figure 4.8. Membership function graphic for HG

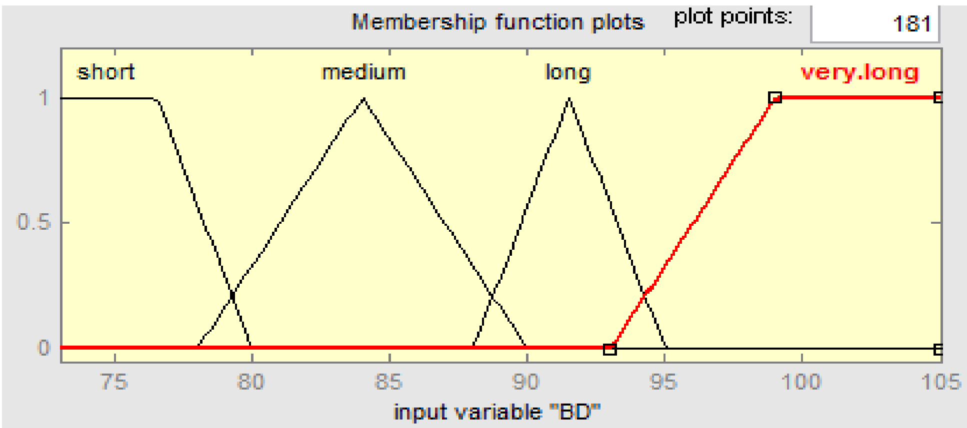


Figure 4.9. Membership function graphic for BD

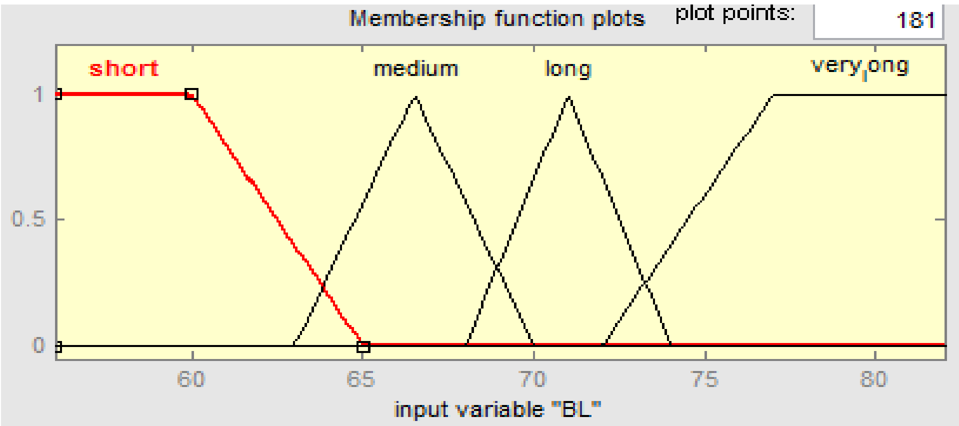


Figure 4.10. Membership function graphic for BL

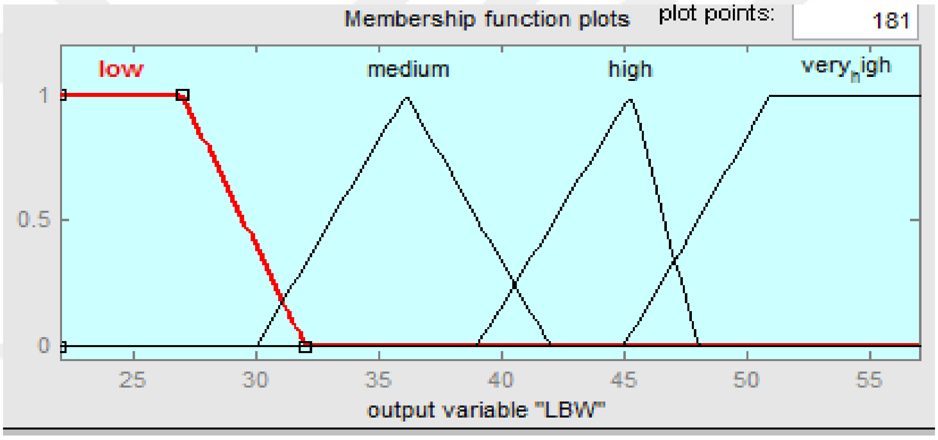


Figure 4.11. Membership function graphic for LBW

4.3. Fuzzy rules

As can be seen from the Table 4.4 the system knowledge base was constituted from 29 rules.

Table 4.4. Rule sets for the FES

Rule No		HG		BD		BL		LBW
1	IF	Short	AND	Medium	AND	Short	THEN	Low
2	IF	Short	AND	Short	AND	Short	THEN	Low
3	IF	Short	AND	Medium	AND	Medium	THEN	Medium
4	IF	Short	AND	Long	AND	Medium	THEN	Medium
5	IF	Medium	AND	Medium	AND	Long	THEN	Medium
6	IF	Medium	AND	Medium	AND	Medium	THEN	Medium
7	IF	Medium	AND	Medium	AND	Short	THEN	Medium
8	IF	Medium	AND	Long	AND	Medium	THEN	High
9	IF	Medium	AND	Long	AND	Short	THEN	Medium
10	IF	Medium	AND	Very long	AND	Long	THEN	High
11	IF	Medium	AND	Short	AND	Medium	THEN	Medium
12	IF	Medium	AND	Short	AND	Long	THEN	Medium
13	IF	Medium	AND	Long	AND	Long	THEN	High

14	IF	Long	AND	Long	AND	Medium	THEN	Medium
15	IF	Long	AND	Medium	AND	Short	THEN	Medium
16	IF	Long	AND	Medium	AND	Medium	THEN	High
17	IF	Long	AND	Very long	AND	Long	THEN	High
18	IF	Long	AND	Long	AND	Long	THEN	High
19	IF	Long	AND	Very long	AND	Medium	THEN	High
20	IF	Long	AND	Very long	AND	Short	THEN	Medium
21	IF	Long	AND	Medium	AND	Long	THEN	Medium
22	IF	Very long	AND	Very long	AND	Long	THEN	High
23	IF	Very long	AND	Very long	AND	Very long	THEN	Very high
24	IF	Very long	AND	Very long	AND	Medium	THEN	High
25	IF	Very long	AND	Long	AND	Medium	THEN	High
26	IF	Very long	AND	Short	AND	Medium	THEN	Medium
27	IF	Very long	AND	Long	AND	Very long	THEN	Very high
28	IF	Very long	AND	Long	AND	Long	THEN	High
29	IF	Very long	AND	Long	AND	Very long	THEN	High

For example, Rule 10 from the table can be explained as follows: If HG is medium and BD is very high and BL is long then LBW is high.

4.4. Inference method

Mamdani inference method was chosen as the inference method. Due to Mamdani max- min method is applied, the λ accuracy ratios for each rule is determined.

$\lambda_1 = \min\{\mu_S(\mathrm{x}), \mu_M(\mathrm{y}), \mu_S(\mathrm{z})\}$ $\lambda_2 = \min\{\mu_S(\mathrm{x}), \mu_S(\mathrm{y}), \mu_S(\mathrm{z})\}$ $\lambda_3 = \min\{\mu_S(\mathrm{x}), \mu_M(\mathrm{y}), \mu_M(\mathrm{z})\}$

$\lambda_4 = \min\{\mu_S(\mathrm{x}), \mu_L(\mathrm{y}), \mu_M(\mathrm{z})\}$ $\lambda_5 = \min\{\mu_M(\mathrm{x}), \mu_M(\mathrm{y}), \mu_L(\mathrm{z})\}$ $\lambda_6 = \min\{\mu_M(\mathrm{x}), \mu_M(\mathrm{y}), \mu_M(\mathrm{z})\}$

$\lambda_7 = \min\{\mu_M(\mathrm{x}), \mu_M(\mathrm{y}), \mu_S(\mathrm{z})\}$ $\lambda_8 = \min\{\mu_M(\mathrm{x}), \mu_L(\mathrm{y}), \mu_M(\mathrm{z})\}$ $\lambda_9 = \min\{\mu_M(\mathrm{x}), \mu_L(\mathrm{y}), \mu_S(\mathrm{z})\}$

$\lambda_{10} = \min\{\mu_M(\mathrm{x}), \mu_{VL}(\mathrm{y}), \mu_L(\mathrm{z})\}$ $\lambda_{11} = \min\{\mu_M(\mathrm{x}), \mu_S(\mathrm{y}), \mu_M(\mathrm{z})\}$ $\lambda_{12} = \min\{\mu_M(\mathrm{x}), \mu_S(\mathrm{y}), \mu_L(\mathrm{z})\}$

$\lambda_{13} = \min\{\mu_M(\mathrm{x}), \mu_L(\mathrm{y}), \mu_L(\mathrm{z})\}$ $\lambda_{14} = \min\{\mu_L(\mathrm{x}), \mu_L(\mathrm{y}), \mu_M(\mathrm{z})\}$ $\lambda_{15} = \min\{\mu_L(\mathrm{x}), \mu_M(\mathrm{y}), \mu_S(\mathrm{z})\}$

$\lambda_{16} = \min\{\mu_L(\mathrm{x}), \mu_M(\mathrm{y}), \mu_M(\mathrm{z})\}$ $\lambda_{17} = \min\{\mu_L(\mathrm{x}), \mu_{VL}(\mathrm{y}), \mu_L(\mathrm{z})\}$ $\lambda_{18} = \min\{\mu_L(\mathrm{x}), \mu_L(\mathrm{y}), \mu_L(\mathrm{z})\}$

$\lambda_{19} = \min\{\mu_L(\mathrm{x}), \mu_{VL}(\mathrm{y}), \mu_M(\mathrm{z})\}$ $\lambda_{20} = \min\{\mu_L(\mathrm{x}), \mu_{VL}(\mathrm{y}), \mu_S(\mathrm{z})\}$ $\lambda_{21} = \min\{\mu_L(\mathrm{x}), \mu_M(\mathrm{y}), \mu_L(\mathrm{z})\}$

$\lambda_{22} = \min\{\mu_{VL}(\mathrm{x}), \mu_{VL}(\mathrm{y}), \mu_L(\mathrm{z})\}$ $\lambda_{23} = \min\{\mu_{VL}(\mathrm{x}), \mu_{VL}(\mathrm{y}), \mu_{VL}(\mathrm{z})\}$ $\lambda_{24} = \min\{\mu_{VL}(\mathrm{x}), \mu_{VL}(\mathrm{y}), \mu_M(\mathrm{z})\}$

$\lambda_{25} = \min\{\mu_{VL}(\mathrm{x}), \mu_L(\mathrm{y}), \mu_M(\mathrm{z})\}$ $\lambda_{26} = \min\{\mu_{VL}(\mathrm{x}), \mu_S(\mathrm{y}), \mu_M(\mathrm{z})\}$ $\lambda_{27} = \min\{\mu_{VL}(\mathrm{x}), \mu_L(\mathrm{y}), \mu_{VL}(\mathrm{z})\}$

$\lambda_{28} = \min\{\mu_{VL}(\mathrm{x}), \mu_L(\mathrm{y}), \mu_L(\mathrm{z})\}$ $\lambda_{29} = \min\{\mu_{VL}(\mathrm{x}), \mu_L(\mathrm{y}), \mu_{VL}(\mathrm{z})\}$

4.5. Defuzzification

In the defuzzification process, crisp outputs were obtained by using the Centroid method according to the degree of accuracy. For example, 43.8 kg LBW was achieved in the developed fuzzy expert system in response to 95 cm HG, 95 cm BD and 70 cm BL. The actual weight of this animal was 43.6 kg. The fuzzy expert system result obtained for these inputs is given in Figure 4.12.

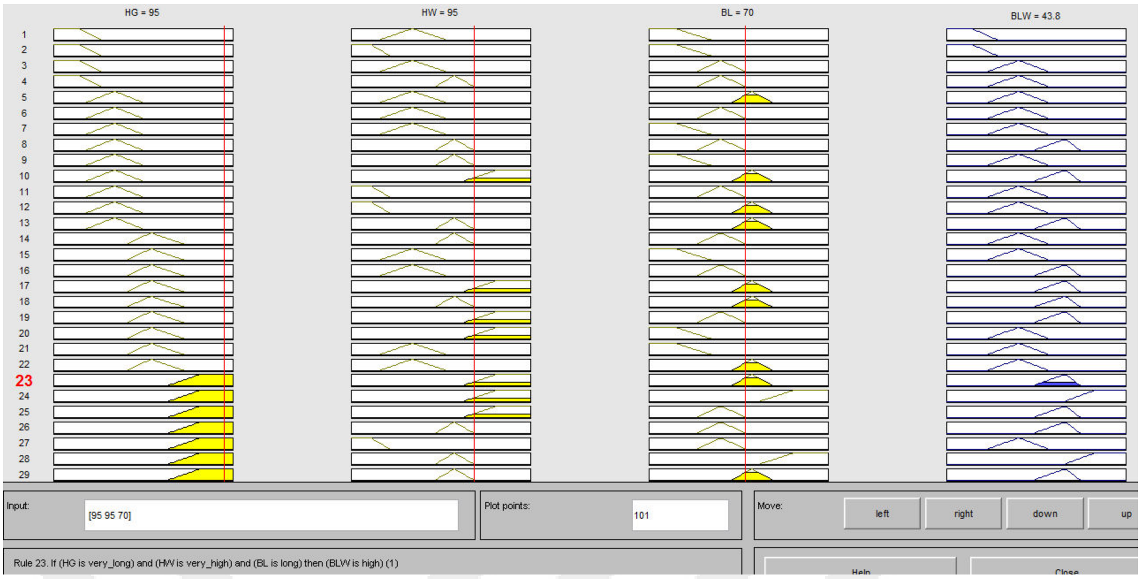


Figure 4.12. Result of FES

For the inputs 95 cm HG, 95 cm BD and 70 cm BL just Rule No 23 was fired. Let's look at another example:

The measurements of the animal like that: HG is 85 cm, BD is 86 cm and BL is 64 cm, LBW=39.9 kg was achieved from the developed fuzzy expert system. The fuzzy expert system result obtained for these values is shown in Figure 4.13. For these inputs 3 rule was fired at the same time. Rule 15 and Rule 16 will be fired at the same time. LBW for Rule 15 is Medium, for Rule 16 is High. In this case, the inference will be calculated as the maximums of the accuracy grades of two fired rules:

Rule 15: $\lambda_{15} = min\{\mu_L(x), \mu_M(y), \mu_S(z)\} = min\{0.5, 0.8, 0.2\} = 0.2$

Rule 16: $\lambda_{16} = min\{\mu_L(x), \mu_M(y), \mu_M(z)\} = min\{0.5, 0.8, 0.2\} = 0.2$

$\lambda = \max\ \{0.2, 0.2\} = 0.2$

Then using centroid method we can calculate the BWL as 39.9 kg.

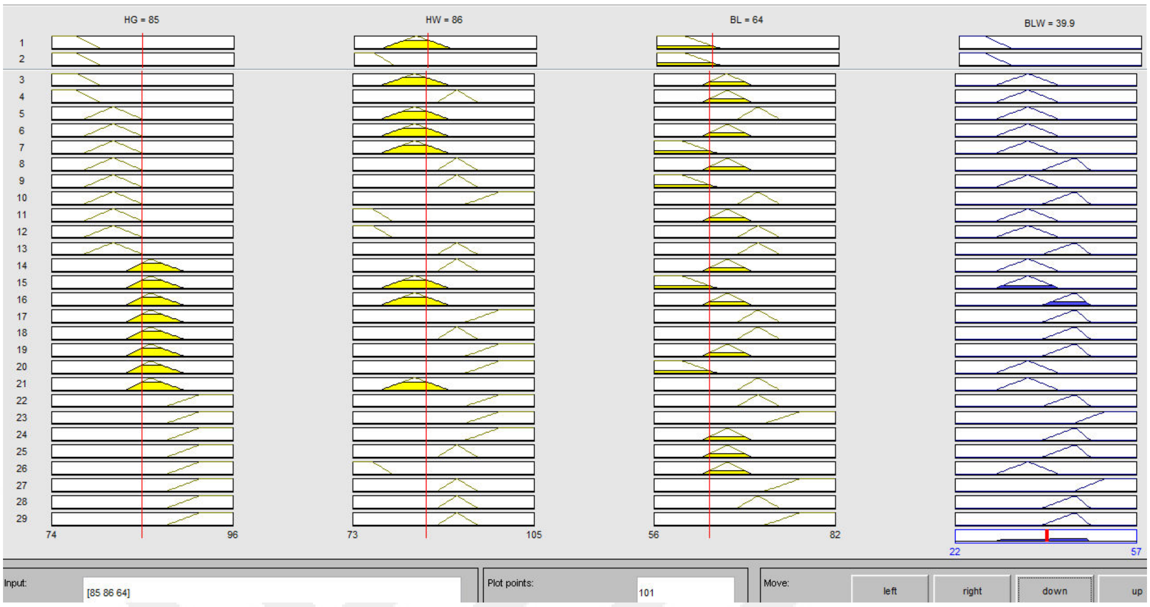


Figure 4.13. Case, where two rules are fired at the same time

After performing this simulation for all goats, it was possible to compare values obtained from FES with the weighed LBW (Figure 4.14).

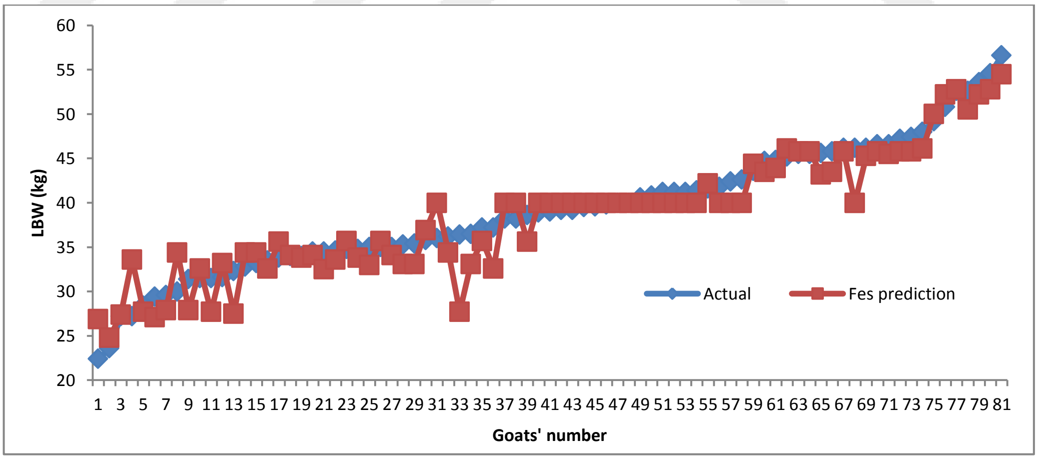


Figure 4.14. Comparison of Actual and FES predicted LBWs

Pearson correlation coefficient between the actually and predicted data calculated as 0.95, which represents a high positive correlation between these sets and indicates that the proposed method is suitable for the LBW prediction (Figure 4.15).

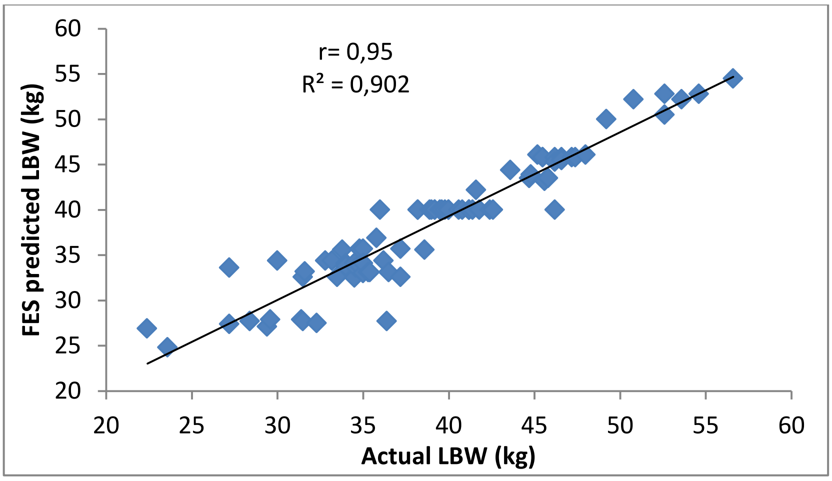


Figure 4.15. Correlation between Actual and FES predicted LBWs

Determination coefficient of the model was calculated as 0.90. The MPE, MAPE and RMSE values calculated as, 1.31, 4.73 and 6.91, respectively.

5. CONCLUSION AND RECOMMENDATIONS

5.1. Conclusions

In this study, general information of fuzzy logic and expert systems was given and various applications in livestock were mentioned in the frame of this information. At the same time, traditional methods for live body weight predictions was investigated. Results obtained from Fuzzy Espert System was better than the results obtained from conventional multiple regression models.

In this study, 81 experimental data were used to estimate live body weight, with the linear body measurements (heart girth, body depth and body length). Experimental data were compared with results obtained with the fuzzy expert system. It was observed that the designed FES results were highly correlated with the experimental data and %90 was confirmed.

5.2. Recommendations

Another feature of the designed fuzzy expert system is that results can be obtained for input values not included in the experimental data. Much better results can be obtained in the subsequent studies with increasing the number of input and output parameters and the number of linguistic variables. Also Sugeno inference system should be applied in FES development in future works.

The usage of FES modeling may be highly recommended to predict LBW instead of time consuming experimental studies.

6. REFERENCES

Abegaz, S., Awgichew, K., 2009. Estimation of weight and age of sheep and goats. Technical Bulletin No23. http://www.esgpip.org/PDF/Technical%20bulletin%20No.23.pdf

Alizadeh, H., Hasani-Bafarani, A., Parvin, H., Minaei, B., Kangavari, M. R., 2008. Dairy Cattle Judging: An Innovative Application for Fuzzy Expert System. Proceedings of the World Congress on Engineering and Computer Science. WCECS 2008, October 22 - 24, 2008, San Francisco, USA.

Allahverdi, N., 2002. Uzman Sistemler. Bir yapay zeka uygulaması (Expert Systems. Application of an Artificial Intelligence). Atlas Yayın Dağıtım, İstanbul.

Anonymous a, 2017. TÜIK – yıllara göre küçükbaş hayvan sayıları. Online: http://www.tuik.gov.tr/PreIstatistikTablo.do?istab_id=682

Anonymous b, 2017. Siirt Kültür ve Turizm Müdürlüğü, Siirt ilinin coğrafi ve iklim özellikleri. Online: https://www.google.com.tr/url?sa=t&rct=j&q=&esrc=s&source=web&cd=6&cad=rja&uact=8&ved=0ahUKEwjh6KKRyYvUAhVMVRQKHbWrDd0QFgg-MAU&url=http%3A%2F%2Fwww.siirtkulturturizm.gov.tr%2FTR%2C56324%2Fcografi-konumu.html&usg=AFQjCNEQwpSIxSETMZ5OdhDPad0U0KDIAQ

Anonymous c, 2017. Meteoroloji Genel Müdürlüğü -Siirt ilinin yıllara göre yağış miktarları. Online: https://www.mgm.gov.tr/veridegerlendirme/yillik-toplam-yagis-verileri.aspx?m=siirt#sfB

Anonymous d, 2017. Siirt Kültür ve Turizm Müdürlüğü Siirt ilinde hayvancılık http://www.siirtkulturturizm.gov.tr/TR,56337/hayvancilik.html

Baykal, N., Beyan, T., 2004. Bulanık Mantık Uzman Sistemler ve Denetleyiciler. (Fuzzy Logic Expert Systems and Controllers). Bıçaklar Kitabevi, Ankara.

Black, M., 1937. Vagueness: An exercise in logical analysis. Philosophy of Science,4, 427–455.

Castillo, E., Gutierrez, J. M., Hadi, A. S., 1997. Expert Systems and probabilistic network models. Springer-Verlag, New York Inc.

Cavero, D., Tölle, K-H., Buxade, C., Krieter, J., 2006. Mastitis detection in dairy cows by application of fuzzy logic. Livestock Production, 105, 207-213.

Chacon, E., Macedo, F., Velázquez, F., Paiva, S.R, Pineda, E., McManus, C., 2011. Morphological measurements and body indices for Cuban Creole goats and their crossbreds. R. Bras. Zootec., v.40, n.8, p.1671-1679.

Chang, A. M., Hall, L. O., 1992. The validation of fuzzy knowledge-based systems. Fuzzy logic for the management of uncertainty, L.A. Zadeh and J. Kacprzyk, eds, John Wiley, New York, pp. 589–604.

Cox, E., 1999. The fuzzy systems handbook: a practitioner's guide to building, using, and maintaining fuzzy systems, 2nd edn. Academic Press, San Diego, CA.

De Mol, R. M., Woldtf, W. E., 2001. Application of fuzzy logic in automated cow-status monitoring. Journal of Dairy Science, 84, 400–410.

FAO 2014. http://faostat.org.

Filho, L.R.A.G., Cremasco, C.P., Putti, F.F., Chacur, M.G.M., 2011. Application of fuzzy logic for the evaluation of livestock slaughtering. Eng. Agric., Jaboticabal, v.31, n.4, p. 813-825.

Firk, R., Stamer, E., Junge, W., Krieter, J., 2002a. Improving oestrus detection by combination of activity measurements with information about previous oestrus cases. Livestock Production Science, 82, 97–103.

Firk, R., Stamer, E., Junge, W., Krieter, J., 2002b. Automation of oestrus detection in dairy cows: a review cases. Livestock Production Science, 75, 219-232.

Kafkan, İ., Balkan, E., Şalk, M., 2013. Fuzzy logic and applications in geophysics: a seismology example. DEÜ Mühendislik Bilimleri Dergisi 15(2): 15-29.

Li, H., Gupta, M., 1995. Fuzzy logic and intelligent systems. Kluwer Academic Publishers, Boston.

Lukasiewicz, J., 1930. Philosophical remarks on many-valued systems of propositional logic. Reprinted in Selected Works, L. Borkowski, ed., Studies in Logic and the Foundations of Mathematics, North-Holland, Amsterdam, 1970, pp.153–179.

Mahmud, M.A., Shaba, P., Abdulsalam, W., Yisa, H.Y., Gana, J., Ndagi, S., Ndagimba, R., 2014. Live body weight estimation using connon bone lenght and other body linear measurements in Nigerian breed of sheep. J Adv Vet Anim Res.; 1(4): 169-176.

Mahmud, M. A., Shaba P., Zubairu, U.Y., 2014. Live body weight estimation in small ruminants – a review. Global Journal of Animal Scientific Research 2(2):102-108.

Mamdani, E. H., Assilian, S., 1975. An experiment in linguistic synthesis with a fuzzy logic controller, International Journal of Man–Machine Studies, 7(1), 1–13.

Memmedova, N., Keskin, İ., 2009. Hayvancılıkta bulanık mantık uygulamaları. Selçuk Tarım ve Gıda Bilimleri Dergisi, 23 (47): (2009) 89-95.

Memmedova, N., Keskin, İ., Zülkadir, U., 2011. Süt sığırlarında bulanık mantık yöntemi ile örnek ayıklama modelinin oluşturulması. 7. Ulusal Zootekni Bilim Kongresi, Çukurova Üniversitesi, Adana.

Memmedova, N., Keskin, İ., 2011. İneklerde bulanık mantık modeli ile hareketlilik ölçüsünden yararlanılarak kızgınlığın tespiti. Kafkas Üniversitesi Veteriner Fakültesi Dergisi, 17(6), 1003-1008.

Mikail, N., Keskin, I., 2015. Subclinical mastitis prediction in dairy cattle by application of fuzzy logic. Pak. J. Agri. Sci., Vol. 52(4), 1101-1107.

Nabiyev, V., 2005. Yapay Zeka, Problemler-Yöntemler-Algoritmalar (Artificial Intelligence, Problems-Methods-Algorithms), Seçkin Yayıncılık, Ankara.

Negnevitsky, M., 2005. Artificial Intelligence. A Guide to Intelligent Systems. www.pearson-books.com. First published 2002. Second edition published 2005. ©Pearson Education Limited 2002.

Neto, M.M., Naas, I.D.A., Carvalho V.C.D., Conceicao, A.H.Q., 2014. Preventive diagnosis of dairy cow lameness. Eng. Agric., Jaboticabal, v.34, n.3, p.577-589.

Parés-Casanova, P.M., Caballero, M., Perezgrovas, R., 2014. Estimating live weight of Chiapas breed for males and females. Journal of Zoological and Bioscience Research, 1, 4:32-35

Pares P., Caballero. M., Vila, L., 2014. Estimating live weight of sheep of Guatemala by a simple formula. ECORFAN-Journal Experimental Desing. Vol.1 No.1 1-5.

Pesmen, G., Yardımcı, M., 2008. Estimating the live weight using some body measurements in Saanen goats. Arciva Zootechnica 11(4): 30-40.

Sackey, G., Ayizanga, R. A., Yaro, M., Aklesi-Kuma, G., 2013. Estimation of live weight in Djallonke sheep using body measurements. 18th Biennial Conference of the Ghana Society of Animal Production.

Sefeedpari, P., Rafiee, S., Akram, A., 2012. Selecting energy efficient poultry egg producers: a fuzzy data envelopment analysis approach. International Journal of Applied Operational Research 2(2): 77-88.

Semerci, A., Çelik, A. D., 2016. Türkiyede küçükbaş hayvan yetiştiriciliğinin genel durumu. Mustafa Kemal Üniversitesi Ziraat Fakültesi Dergisi. Cilt 21, Sayı 2.

Shirzeyli, F. H., Lavvaf, A., Asadi, A., 2013. Estimation of body weight from body measurements in four breeds of Iranian sheep. Songklanakarin J. Sci. Technol. 35 (5), 507-511.

Solatian, P., Abbasi, S. H., Shabaninia, F., 2012. Simulation study of flow control based on PID ANFIS controller for non-linear process plants. American Journal of Intelligent Systems, 2(5), 104-110.

Strasser, M., 1997. The development of a fuzzy-decision-support system for dairy cattle culling decisions. A thesis of the degree of Master of Science, McGill University.

Sugeno, M., 1985. Industrial Applications of Fuzzy Control. North-Holland, Amsterdam.

Şen, Z., 2001. Bulanık Mantık ve Modelleme İlkeleri. (Principles of Fuzzy Logic and Modeling). Bilge Yayıncılık, İstanbul.

Taşdemir S., Ürkmez, A., İnal, Ş., 2011. A fuzzy rule-based system for predicting the live weight of Holstein cows whose body dimensions were determined by image analysis. Turk J Elec Eng & Comp Sci, Vol. 19, No4. TÜBİTAK.

Tadesse, A., Gebremariam, T., 2010. Application of linear body measurements for live body weight estimation of highland sheep in Tigray region, North – Ethiopia. Journal of the Drylands 3(2): 203-207.

Turan, N., Özyazıcı, M. A., Tantekin, G. Y., 2015. Siirt ilinde çayır mera alanlarından ve yem bitkilerinden elde edilen kaba yem üretim potansiyeli (derleme). Türkiye Tarımsal Araştırmalar Dergisi. Cilt 2. Sayı 1.

Turksen, I. B., Tian, Y., Berg, M., 1992. A fuzzy expert system for a service centre of spare parts. Expert Systems with Applications, 5, 447–464.

Wade, K. M., Lacroix, R., Strasser, M., 1998. Fuzzy logic membership values as a ranking tool for breeding purposes in dairy cattle. Proceedings of the 6th World Congress on Genetics Applied to Livestock Production. Vol. 27, 433-436.

Wang, E., Samarasinghe, S., 2005. On-line detection of mastitis in dairy herds using artificial neural networks. Proceedings of the Modelling and Simulation Congress (International) (MODSIM), Melbourne, Australia.

Wessiania, N. A., Sarwokob, S. O., 2015. Risk analysis of poultry feed production using fuzzy FMEA. Industrial Engineering and Service Science. Procedia Manufacturing 4 (2015) 270–281.

Zadeh, L., 1965. Fuzzy sets, Information and Control, 8(3), 338–353.

Zadeh, L., 1973. Outline of a new approach to the analysis of complex systems and decision processes. IEEE Transactions on Systems, Man and Cybernetics, SMC-3(1), 28–44.

Zadeh, L. A., 2001. Applied Soft Computing-Foreword, Applied Soft Computing, Volume 1, Issue 1.

Zimmermann, H. J., 1987. Fuzzy sets, decision making and expert systems. Kluwer Academic Publishers, Boston.

CURRICULUM VITAE

PERSONAL INFORMATION

Name Surname	Aras Ayoob AMEEN
Birth Place and Date	14.11.1991 / Kirkuk
Telephone	
E-mail	aras_ayoob@yahoo.com

EDUCATION

Certificates		**Name. City. Country**	**Graduation year**
High school	:	Khazi Mahammad High School	20
University	:	Kirkuk University	2012
Graduate School	:		

WORK EXPERIENCE

Year	**Organization**	**Job**

AREA OF SPECIALIZATION

FOREIGN LANGUAGES

Arabic – Turkish – English

OTHER FEATURES YOU WANT TO SPECIFY

PUBLICATIONS