ON THE USE OF FUZZY C-REGRESSION TRUNCATED MODELS FOR HEALTH INDICATOR IN INTENSIVE CARE UNIT

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To my beloved mother, father, wife and children

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IN THE NAME OF ALLAH, THE MOST BENEFICENT AND THE MOST MERCIFUL

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ABSTRACT

Two new techniques for clustering data, namely the fuzzy c-regression truncated models (FCRTM) and fuzzy c-regression least quartile difference (LQD) models (FCRLM) were proposed in this thesis in analyzing a nonlinear model. These new models include their functions, the estimation techniques and the explanation of the five procedures. The stepwise method was used for variable selection in the FCRTM and FCRLM models. The number of clusters was determined using the compactness-to-separation ratio, F_{NEW}. The various values of constant, k (k = 0.1, 0.2, ..., ∞) in generalized distance error and various values of fuzzifier, w ($1< w <3$) were used in order to find the lowest mean square error (MSE). Then, the data were grouped based on cluster and analyzed using truncated absolute residual (TAR) and the least quartile difference (LQD) technique. The FCRTM and FCRLM models were tested on the simulated data and these models can approximate the given nonlinear system with the highest accuracy. A case study in health indicator (simplified acute physiology score II (SAPS II score) when discharge from hospital) at the intensive care unit (ICU) ward was carried out using the FCRTM and FCRLM models as mentioned above. Eight cases of data involving six independent variables (sex, race, organ failure, comorbid disease, mechanical ventilation and SAPS II score when admitted to hospital) with different combinations of variable types in each case were considered to find the best modified data. The comparisons among the fuzzy c-means (FCM) model, fuzzy c-regression models (FCRM), multiple linear regression model, Cox proportional-hazards model, fuzzy linear regression model (FLRM), fuzzy least squares regression model (FLSRM), new affine Takagi Sugeno fuzzy models, FCRTM models and FCRLM models were carried out to find the best model by using the mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE). The results showed that the FCRTM models were found to be the best model, having the lowest MSE, RMSE, MAE and MAPE. This new modelling technique could be proposed as one of the best models in analyzing mainly a complex system. Hence, the health indicator in the ICU ward could be monitored by managing six independent variables and other management quality variables in the hospital management.

ABSTRAK

Dua teknik baru di dalam data kluster, yang dinamakan model terpangkas c-regresi kabur (FCRTM) dan model beza kuartil terkecil (LQD) c-regresi kabur (FCRLM) dicadangkan dalam tesis ini dalam menganalisis model tak linear. Model-model baru ini meliputi fungsi-fungsi, teknik anggaran dan penjelasan tentang lima prosedur. Kaedah langkah demi langkah digunakan dalam pemilihan pembolehubah bagi model FCRTM dan FCRLM. Bilangan kluster ditentukan dengan menggunakan nisbah kepadatan-kepada-pemisahan, F_{NEW}. Pelbagai nilai pemalar, k (k = 0.1, 0,2 , ..., ∞) dalam ralat jarak umum dan pelbagai nilai pekali kabur, w ($1 < w < 3$) telah digunakan untuk mencari nilai terendah ralat kuasa dua min (MSE). Kemudian, data dikumpulkan berdasarkan kluster dan dianalisis menggunakan kaedah ralat mutlak terpangkas dan kaedah beza kuartil terkecil. Model FCRTM dan FCRLM diuji ke atas data simulasi dan model ini boleh menganggar sistem tak linear yang diberikan dengan ketepatan yang lebih tinggi. Satu kajian kes terhadap penunjuk kesihatan (skor II bagi ringkasan akut fisiologi (SAPS II) apabila keluar dari hospital) di wad Unit Rawatan Rapi (ICU) menggunakan model FCRTM dan FCRLM seperti yang dinyatakan di atas telah dijalankan. Lapan kes data yang melibatkan enam pembolehubah tak bersandar (jantina, bangsa, kegagalan organ, penyakit sedia ada, pengudaraan mekanikal dan skor SAPS II apabila dimasukkan ke hospital) dengan gabungan pembolehubah berlainan jenis dalam setiap kes dipertimbangkan untuk mencari data diubahsuai yang terbaik. Perbandingan di antara model c-purata kabur (FCM), model c-regresi kabur (FCRM), model regresi linear berganda, model Cox kadaran-bahaya, model regresi linear kabur (FLRM), model regresi kuasa dua terkecil kabur (FLSRM), model baru kabur hubungan Takagi-Sugeno, model FCRTM dan FCRLM telah dijalankan untuk mencari model terbaik dengan menggunakan MSE, ralat punca kuasa dua min (RMSE), ralat mutlak min (MAE) dan peratus ralat mutlak min (MAPE). Keputusan menunjukkan bahawa model FCRTM menjadi model yang terbaik dengan nilai MSE, RMSE, MAE dan MAPE yang terendah. Teknik pemodelan yang baru ini boleh dicadangkan sebagai salah satu model yang terbaik dalam menganalisis terutamanya sistem yang kompleks. Oleh itu, penunjuk kesihatan di wad ICU boleh dipantau oleh enam pembolehubah tak bersandar dan lain-lain pembolehubah pengurusan kualiti di dalam pengurusan hospital.

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LIST OF ABBREVIATIONS / SYMBOLS

A	-	Any arbitrary number (matrix)
a_0^i	-	Constant for T-S models
$a_j^{'}(b)$	-	Inverse membership function for set A_R
$a_j^{''}(b)$	-	Inverse membership function for set A_L
$a_q^i,\ q = 1,\ldots,g$	-	Individual consequent parameters for T-S models
A	-	Fuzzy set of A
A_p^i		Inappropriate antecedent fuzzy set
A_q^i	-	Individual antecedent fuzzy sets
ACHS	-	Australian Council on Healthcare Standards
AFCRC	-	Adaptive fuzzy c-regression model with convexity enhancement
AHP	-	Analytical hierarchy process
AIDS	-	Acquired Immunodeficiency Syndrome
AMI	-	Acute myocardial infarctions
ANN	-	Artificial neural network
APACHE	-	Acute physiology and chronic health evaluation
b	-	Level of existence corresponds to the level of membership
bigVAT	-	Big VAT
b_g	-	Estimated regression coefficient for all N cases
$b_{g(e)}$	-	Estimated regression coefficient when eth case is omitted
BMI	-	Body mass index
c	-	Number of clusters

ς_i	-	Width for fuzzy parameter i
CABGs	-	Coronary artery bypass grafts
CF	-	Cost function
CI	-	Confidence interval
C_{gg}	-	gth diagonal element of matrix $(\mathbf{X}^{\mathrm{T}}\mathbf{X})^{-1}$
CMP	-	Case mix programme
comorbid	-	Comorbid diseases
C_p	-	Mallows index
CRPS	-	Comparison reference-point shifting
CVDs	-	Cerebrovascular disorders
D	-	Sufficiently small negative number
$\mathbf{D}$	-	New variable as dual variable (matrix)
DEA	-	Data Envelopment Analysis
$DFBETAS_{g(e)}$	-	$DFBETAS$ measure in the eth case
d_{ij}	-	Square inner-product Euclidean distance norm
DMU	-	Decision-making units
$d(p, q)$	-	Chebyshev distance between two vectors or points p and q
$d(P, Q)$	-	Minkowski distance of order k between two points P and Q
DR	-	Deepest regression
DVT	-	Deep venous thrombosis
e	-	Index regression number from 1 to N
E_c	-	Canonical (unit vector) basis of Euclidean c space with crisp (nonfuzzy) labels
ED	-	Emergency department
EEG	-	Electroencephalogram
E_{fc}	-	Subset of a hyperplane (convex hull) with constrained labels
E_{fcu}	-	Unit hypercube in R^c with unconstrained labels
$E_{ij}(\beta_i)$	-	Measure of errors in $f_i(x_j;\beta_i)$

$E_m(U,\{\beta_i\})$	-	Ojective function for FCRM models
EM	-	Expectation maximization
E(ε_i)	-	Expectation of random errors
f	-	Index regression number from 1 to g
F	-	Xie and Beni index
FAMIMO	-	Fuzzy algorithms for the control of Multi-Input Multi-Output processes
FCCM	-	Fuzzy clustering for categorical multivariate data
FCM	-	Fuzzy c-means
f_{com}	-	Compactness validity function
FCRLM	-	Fuzzy c-regression LQD models
FCRM	-	Fuzzy c-regression models
FCRTM	-	Fuzzy c-regression truncated models
FE	-	Fuzzy error
$f^i(x,\theta_i)$	-	Multiple linear regression equation for cluster i
FIS	-	Fuzzy inference system
FKM	-	Fuzzy k-means
FLRM	-	Fuzzy linear regression model
FLSRM	-	Fuzzy least squares regression model
FM	-	Fuzzy minimals
FMLE	-	Fuzzy maximum likelihood estimation
FMLS	-	Fuzzy membership function least-squares
F_{NEW}	-	Compactness-to-separation ratio
FNNS	-	Fuzzy neural network system
f_{sep}	-	Separation validity function
$f(x,\mathbf{A})$	-	Fuzzy function of set $\mathbf{A}$
$f(\mathbf{X},\mathbf{A})$	-	Fuzzy model
g	-	Number of independent variables

GA	-	Genetic algorithm
GCS	-	Glasgow coma score
geFFCM	-	Generalized extensible fast fuzzy c-means
GFLM	-	General fuzzy linear model
GI	-	Gastro intestinal
GK	-	Gustafson-Kessel
GNP	-	Gross national product
h or H	-	Level sets or degree of the fitting of the fuzzy linear model by the decision maker
$\mathbf{H}$	-	Leverage hat matrix
h_{ee}	-	Leverage value for *e*th observation
$\overline{h}_e$	-	Index for level sets
HIV	-	Human Immunodeficiency Virus
HR	-	Hazard ratio
I	-	Index fuzzy number from 1 to c
$\mathbf{I}$	-	Induced the standard Euclidean norm (matrix)
IC	-	Integrated circuit
ICNARC	-	the Intensive Care National Audit & Research Centre
ICU	-	Intensive care unit
I_G	-	Fuzzy clustering validity function
I_j	-	The event when i is between 1 and c and $E_{ij} = 0$
inf	-	Infremum
ISODATA	-	Iterative Self-Organizing Data Analysis Technique
IWS	-	Invariable weights system
JM	-	Judgment matrices
j	-	Index fuzzy number from 1 to N
$J(\mathbf{X};U,V)$ or J	-	Objective function for FCM model
JJ	-	Vagueness of fuzzy linear

ll	-	Constant in fuzzy linear regression model
k	-	Index fuzzy number from 1 to c
kk	-	Order kk in Minkowski distance
k_1, k_2	-	Small real positive constants
l	-	Iteration number
L	-	Left reference function
LFA	-	Logical framework analysis
LIFE	-	Laboratory for International Fuzzy Engineering
LMI	-	Linear matrix inequality
LMS	-	Least median of squares
LOS	-	Length of stay
LQD	-	Least quartile difference
LQS	-	Least quartile of squares
LR	-	Logistic regression
LS	-	Least square
LTS	-	Least trimmed squares
m	-	Number of alternatives in AHP technique
max	-	Maximum value of each rule output set
MAP	-	Mean arterial pressure
M_{cn}	-	Sets of crisp c-partitions of S
MCTDCFCRM	-	Multi-Channels Time-Domain-Constrained FCRM
mecvent	-	Mechanical ventilator
MEDLINE	-	Medical literature analysis and retrievel system online (Journal citations and abstracts for biomedical literature from around the world)
MF	-	Membership function
M_{fcn}	-	Sets of constrained of S
M_{fcnu}	-	Sets of unconstrained of S
MLR	-	Multiple linear regression

MICU	-	Medical intensive care unit
MPG	-	Miles per gallon
MPM	-	Mortality probability models
MRO	-	Multi-criteria Rank Ordering
MSE	-	Mean square error
MSE_e	-	Mean square error with the deleted *e*th observation
n	-	Number of factors in AHP technique
N	-	Number of observations
n_i	-	Normal vector of the *i*-th linear hyper-plane or $[a_1^i,\ldots,a_n^i,-1]^{\mathrm{T}}$
N	-	Normal distribution
N	-	Number of observations
NARX	-	Nonlinear autoregressive exogenous model
NICU	-	Neonatal intensive care unit
OERI	-	Overall existence ranking index
$OM(A_j)$	-	OERI function for set A_j
COR	-	Crude odds ratio
OR	-	The algebraic sum of each rules output set
orgfail	-	Organ failures
p	-	Number of independent variables + 1
P	-	Factor in FLSRM membership function
pd	-	Probability distribution function
PRO	-	Peer review organization
PUD	-	Peptic ulcer disease
QQ plot	-	Quartile-quartile plot
R	-	Right reference function
R^2 or r^2	-	Coefficient of determination
$\overline{R}^2$ or $\overline{r}^2$	-	Adjusted version of R^2
R_C	-	Mandani’s fuzzy implication

R^c	-	Dimension in *c* space
rd	-	Random digit
reVAT	-	Revised VAT
RFRA	-	Robust fuzzy regression agglomeration
R^i	-	*i*th for IF-THEN rule
R_g^2	-	Coefficient of determination when X_g is regressed on the *p*-2 other *X* variables in the model
ROC	-	Receiver operator characteristic
RPCA	-	Robust parallel competitive agglomerative
RPSFR	-	Robust Proper Structure Fuzzy Regression
R^p	-	Dimension in *s* and *t* space (*x* and *y* axis)
RR	-	Relative risk
R^s	-	Dimension in *s* space (*x* axis)
R^t	-	Dimension in *t* space (*y* axis)
S	-	Data set of (x_i, y_i)
s2sadm	-	Score of SAPS II admit
s2sdisc	-	Score of SAPS II discharge from hospital
SAPS II	-	Simplified acute physiology score II
SAS	-	Statistical Analysis System
SETAR	-	Self-Exciting Threshold Autoregressive
SGA	-	Standard genetic algorithm
SISO	-	Single-input single-output
sum	-	Sum of each rules output set
sup	-	Supremum
Supp	-	Support of the fuzzy set
TDCFCRM	-	Time-Domain-Constrained FCRM
t_e	-	Studentized deleted residual for *e*th observation
TS	-	Takagi-Sugeno

TSK	-	Takagi-Sugeno-Kang
u	-	Vector u
$\mathbf{U}$	-	Membership function (matrix)
UFP-ONC	-	Unsupervised fuzzy partition-optimal number of classes
u_{ij}	-	Membership values or fuzzy partition matrix of $\mathbf{X}$
UJB	-	Unintentional judgmental bias
UN	-	United Nations
VAT	-	Visual Assessment of Tendency
v_i	-	Corresponding unit normal vector i of each linear hyper-plane or center of the i^{th} cluster
v_k	-	Corresponding unit normal vector k of each linear hyper-plane or center of the k^{th} cluster
VIF	-	Variation inflation factor
V_{PC}	-	Bezdek's partition coefficient
w	-	Fuzzifier or fuzzy weighting
WBC	-	White blood count or number
$w^i(\mathbf{x})$	-	Degree of completion of the antecedent
$\mathbf{XX}$	-	Cluster centre
$\mathbf{X}$	-	Independent variable (matrix)
x_j	-	Independent variable ($j = 1,\ldots, N$)
X_{ef}	-	Independent variables with index e and f
X_{ij}	-	Independent variables with index i and j
$x_q,\ q = 1, \ldots, g$	-	Individual input variables
$\mathbf{X}^{\mathrm{T}}$	-	Transpose for matrix $\mathbf{X}$
$\mathbf{Y}$	-	Dependent variable (matrix)
Y_e	-	Dependent variable for eth observation
Y_i	-	Dependent variable for ith observation
y^i	-	Output of each rule
z_i	-	Tranpose data of (x_i, y_i)

Z	-	Variable for standardized normal distribution
$\Im$	-	Infinite dimensional feature space
$\forall$	-	For every
β_f	-	Coefficient in multiple linear regression model
ε_e	-	Random errors for *e*th observation
$\sim$	-	Follow
$\boldsymbol{\beta}$	-	Unknown coefficient (matrix)
$\boldsymbol{\varepsilon}$	-	Random errors (matrix)
$\left.\frac{\delta S}{\delta \boldsymbol{\beta}}\right\|_{\hat{\boldsymbol{\beta}}}$	-	Differentiate S with respect to β
$\hat{\boldsymbol{\beta}}$	-	Least squares estimator
$\mu_A(x)$	-	Membership function of element x in set A
Δ	-	Termination tolerance
Σ	-	Covariance matrix
μ	-	Mean of z
σ^2	-	Variance of z
Ω	-	Set of feasible values of $\boldsymbol{\beta}$
$\beta^*{}_1,....\beta_c^*$	-	Good switching regressions parameters
ζ	-	Transpose matrix of $[x_1, x_2, ..., x_N, y]$
β_{ik}	-	Shift term between y_j and y
α_q^i	-	Mean for membership function for cluster i
β_q^i	-	Standard deviation for membership function for cluster i
α_q^k	-	Mean for membership function for cluster k
β_q^k	-	Standard deviation for membership function for cluster k
$\delta(j)$	-	Difference between the sampled output $y(j)$ and the fuzzy model output $\hat{y}(j)$
ϕ^i	-	Normalised degree of fulfillment for each rule
η_1 and η_2	-	Positive real-valued constants denoting the step-size

$\varepsilon_{\alpha\beta}$	-	Termination threshold for antecedent parameter
ε_{ab}	-	Termination threshold for consequent parameter
α	-	Center for fuzzy parameter
$\boldsymbol{\alpha}'$	-	New variable for α
$\omega(b)$	-	Subjective weighting function for b
$\chi_1(b)$	-	Subjective weighting factors for $a_j^{'}(b)$
$\chi_2(b)$	-	Subjective weighting factors for $a_j^{''}(b)$
λ	-	Level set for FLSRM model
$\vert\ \vert_\Gamma$	-	λ - level set
$S(\beta)$	-	Function for least squares method
$\mathbf{U}^*$	-	Reasonable fuzzy partitioning
$\vert\langle v_i, v_k\rangle\vert$	-	Absolute value of the standard inner-product of their unit normal vectors
$V(\varepsilon_e)$	-	Variance of random errors
y_i^*	-	Estimated value for y
$\hat{y}$	-	Output of fuzzy model

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CHAPTER 1

INTRODUCTION

1.1 Introduction

This chapter presents the introduction to this thesis. It begins by describing the overall research background followed by a brief history of the intensive care unit (ICU) in Malaysia. Problem descriptions, research objectives, scope of the study, research importance and research contribution are also given. Finally, a brief description of each chapter is stated.

1.2 Research Background

Lotfi A. Zadeh from University of California at Berkeley was the first to propose fuzzy logic in 1965 with a fuzzy set theory. Fuzzy logic, when interpreted in a wider sense, is the theory of fuzzy sets. The concept of fuzzy sets provides a convenient way to represent various notions with imprecision, vagueness, or fuzziness, e.g. young, tall, cold, etc., which we frequently employ in our everyday life. As such, fuzzy logic has the rationale of more closely resembling than traditional logic the way human beings actually think, where alternatives are not black and white but shades of gray. Fuzzy logic has had notable success in various engineering applications.

When interpreted in a narrower sense, fuzzy logic is an extension of ordinary two-valued logic in such a way that the points in interval units are allowed as truth-values. As the truth-values are generalized in such a way, usual truth-functional operations are generalized accordingly. Fuzzy logic is controversial in some circles, despite wide acceptance and a broad track record of successful applications. It is rejected by some control engineers for validation and other reasons, and by some statisticians who hold that probability is the only exact mathematical description of uncertainty. Critics also argue that it cannot be a superset of ordinary set theory since membership functions are defined in terms of conventional sets.

Fuzzy logic is a form of many-valued logic or probabilistic logic; it deals with reasoning that is approximate rather than fixed and exact. In contrast with traditional logic theory, where binary sets have two-valued logic: true or false, fuzzy logic variables may have a truth value that ranges in degree between 0 and 1. Fuzzy logic has been extended to handle the concept of partial truth, where the truth value may range between completely true and completely false. Furthermore, when linguistic variables are used, these degrees may be managed by specific functions.

Fuzzy logic has been applied to many fields, from control theory to artificial intelligence. The reasoning in fuzzy logic is similar to human reasoning. It allows for approximate values and inferences as well as incomplete or ambiguous data (fuzzy data) as opposed to only relying on crisp data (binary choices). Fuzzy logic is able to process incomplete data and provide approximate solutions to problems other methods find difficult to solve.

Fuzzy logic and probabilistic logic are mathematically similar. Both have truth values ranging between 0 and 1, but conceptually distinct, due to different interpretations. Fuzzy logic corresponds to “degrees of truth”, while probabilistic logic corresponds to “probability and likelihood”. As these values differ, fuzzy logic and probabilistic logic yield different models of the same real-world situations. Fuzzy logic and probability are different ways of expressing uncertainty. While both fuzzy logic and probability theory can be used to represent subjective belief, fuzzy set theory uses the concept of fuzzy set membership (i.e., how much a variable is in a set), and probability theory uses the concept of subjective probability (i.e., how probable/ possible do I think that a variable is in a set).

In statistics, fuzzy model was initiated by Tanaka (1982) who introduced fuzzy linear regression model. In his study, he concentrated on the application of fuzzy linear function to a regression analysis in a vague phenomenon. In the usual regression model, deviations between the observed values and the estimated values are supposed to be due to observation errors which must meet the normal distribution. However, Tanaka assumed that these deviations or these fuzziness of system parameters depend on the vagueness of the system structure. In other words, the deviations are closely related to fuzziness of system parameters rather than observation errors. We consider our data as input-output relations whose vagueness of the system structure expressed by fuzzy parameters.

A significant advantage in the use of fuzzy model is that it can be used without the need for early assumptions. If the error for a certain data is not normally distributed, fuzzy model can still be used. In fact, many of the actual data around us do not have a normal distribution. This contrasts with the multiple linear regression model in which normality assumption of the residuals should be met first before using multiple linear regression model. Therefore, all data types can be used in the fuzzy model.

Here are other uses of fuzzy logic in our everyday life such as air conditioners, cameras, digital image processing, rice cookers, dishwashers, elevators, washing machines and other home appliances, video game artificial intelligence, language filters on message boards and chat rooms for filtering out offensive text, pattern recognition in Remote Sensing, automobile and other vehicle subsystems (such as ABS and cruise control e.g. Tokyo monorail) and the massive engine used in the new films, which helped show huge scale armies.

There are many advantages of using fuzzy model. Fuzzy model is conceptually easy to understand. The mathematical concepts behind fuzzy reasoning are very simple. What makes fuzzy interesting is the naturalness of its approach and not its far-reaching complexity. Fuzzy logic is flexible. With any given system, it is easy to manage it or layer more functionality on top of it without starting again from scratch. Fuzzy logic is tolerant of imprecise data. Everything is imprecise if you look closely enough, but more than that, most things are imprecise even on careful inspection. Fuzzy reasoning builds this understanding into the process rather than tacking it onto the end.

Fuzzy logic can model nonlinear functions of arbitrary complexity. You can create a fuzzy system to match any set of input-output data. This process is made particularly easy by adaptive techniques like ANFIS (Adaptive Neuro-Fuzzy Inference Systems), which are available in the Fuzzy Logic Toolbox. Fuzzy logic can be built on top of the experience of experts. In direct contrast to neural networks, which take training data and generate opaque, impenetrable models, fuzzy logic lets you rely on the experience of people who already understand your system. Fuzzy logic can be blended with conventional control techniques. Fuzzy systems do not necessarily replace conventional control methods. In many cases fuzzy systems expand them and simplify their implementation. Fuzzy logic is based on natural language. The basis for fuzzy logic is the basis for human communication.

Fuzzy modelling is applicable and a very vital computational model for a wide variety of problems. These include pattern recognition, function approximation, image processing, clustering, prediction and forecasting. It is a common practice to use the trial and error method to find an appropriate fuzzy modelling for a given problem. Modelling helps to make predictions more precise. There is no doubt that modelling will preserve its importance in medical research as the problems become more complex and difficult.

1.3 A Brief History of Intensive Care Unit in Malaysia

Intensive care for the critically ill patients is a necessary component of acute hospital care. Although intensive care unit patients account for only 5% of in total patients, it contributes a significant amount of health care resources. In the United States, it accounts for 1% of the Gross National Product (GNP) and 15-20% of whole hospital cost. This economic and institutional cost has increased the needs for outcome evaluation and quality assurance. Clinical audits can provide a purpose assessment of performance, effectiveness of therapy and utilisation of resources.

The first ICU in Malaysia was established in 1968. Since then, intensive care unit has grown rapidly and it is now available in all tertiary care hospitals and selected secondary care hospitals in the Ministry of Health. Rapid development of medical and surgical subspecialties in the last decade resulted in increasing demands for more ICU beds and provides momentum for its development. In a recent national mortality audit, the lack of intensive care beds has been cited as a major contributing factor in perioperative deaths (mortality in relation to surgery, often defined as death within two weeks of a surgical procedure) in the Ministry of Health hospitals.

The condition in the United Kingdom in the early 1980's was similar to what we are currently experiencing in Malaysia. There was a great stress on the hospital services as the demand for intensive care beds increases. More ICU beds were opened up and high dependency units increased rapidly without proper assessment for their needs. This chaotic development and the resulting of unequal distributions of the facilities and poor patient outcome encouraged a call for a national audit.

Therefore in 1994, the Intensive Care National Audit & Research Centre (ICNARC) was established in UK. It was sponsored by the intensive Care Society and the Department of Health. Its major mission was to conduct a review on intensive care practice using a Case Mix Programme (CMP) and to make suggestion to the relevant health authorities. The findings of ICNARC and that of the National Expert Group for the Department of Health prompted the British government to spend £142.5 million in year 2000 to further improve intensive care throughout the country. Through the CMP, the ICNARC also created a national database made available to the clinicians and hospital managers for clinical review and planning purposes.

In Australia and New Zealand, clinical indicators in intensive care were developed by representatives of the Australian and New Zealand Intensive care professional bodies and the Australian Council on Healthcare Standards (ACHS) to assess key aspects of intensive care functions within a hospital. In Malaysia, The National Audit on Adult Intensive Care Units is organized in 2002 and modelled on the UK experiences. It is a quality improvement activity supported by the Bahagian Perkembangan Perubatan and organized by a national committee comprising of senior intensive care specialists in the Ministry of Health. This audit consists of two parts. Part 1 is a review of the clinical practice of intensive care by way of developing a national database. Part II is to assess three fundamental aspects of intensive care functions within a hospital. They are the sufficiency of the intensive care resource to meet hospital requirements, the comparison of patient outcome with a national and/or international standard and the evaluation of complications of treatment.

Assessment of the three fundamental aspects in intensive care unit is important to the practitioners and function of an intensive care unit within a hospital. Selection of indicators that address them is hard. There are many indicators that could assess each of these areas. For the sake of ease and simplicity, we accept the clinical indicators developed by ACHS (The Australian Council on Healthcare Standard). A clinical indicator is a measure of the clinical management and outcome of care and should be a useful instrument for clinicians to flag potential problems and areas for improvement (The Committee for National Audit on Adult Intensive Care Units, 2002).

1.4 Problem Statement

Intensive care practice is well established in Malaysia. The study on the ICU was conducted in detail in 2002 by The Committee for National Audit on Adult Intensive Care Units. Clinical practice, performance and outcome have been published. The outcomes of intensive care in Ministry of Health ICUs have been compared with other parts of the world. A clinical indicator developed by ACHS is used in Malaysian hospitals to identify potential problems and for improvement of service. ICU mortality rates are predicted using the logistic model in which the main factor contributing to mortality is simplified acute physiology score II (SAPS II) when discharge from hospital (s2sdisc). However, it serves only as a medical report with no further action taken to reduce the death rate based on the conclusions from the data analysis. For example, the motto in treating the patients who are really in critical condition. So far, no mechanism is used to identify and treating high-risk patients first.

In fuzzy c-regression models (FCRM), there are two important factors, namely the fuzzy model (fuzzification and defuzzification) and the multiple linear regression (MLR) model. Both factors are closely associated in producing the final fuzzy c-regression models (FCRM). In this case, the MLR model used is the basic model without considering the problem of outlier data. So, FCRM models common issue is that it is vulnerable to outlier data. In any statistical studies, researchers want to find the latest methods in reducing the value of the error. Several current methods of addressing outlier in the MLR model which are robust against outliers can be adapted in FCRM models.

1.5 Research Objectives

This research is an attempt to present a proper methodology and analysis of modelling health indicator in the ICU. The objectives of this study are detailed as below;

(i) To apply the data mining technique, that is, the analytical hierarchy process (AHP) method in order to fuzzify binary health indicator data into continuous data.

(ii) To identify the critical point of health indicator using fuzzy c-means (FCM) model so as to categorize patients into "high risk" or "non-high risk" patients.

(iii) To apply the existing models such as multiple linear regression (MLR) model and fuzzy models specifically fuzzy linear regression model (FLRM), fuzzy least squares regression model (FLSRM), fuzzy c-regression models (FCRM) and new affine Takagi Sugeno fuzzy models for the health indicator in the ICU.

(iv) To propose two new models which are fuzzy c-regression truncated models (FCRTM) and fuzzy c-regression LQD (least quartile difference) models (FCRLM) for the health indicator in the ICU.

(v) To make comparison among the models in order to find the best model in modelling health indicator.

These objectives will be achieved by following the research framework as shown in Figure 1.1 and Figure 1.2.

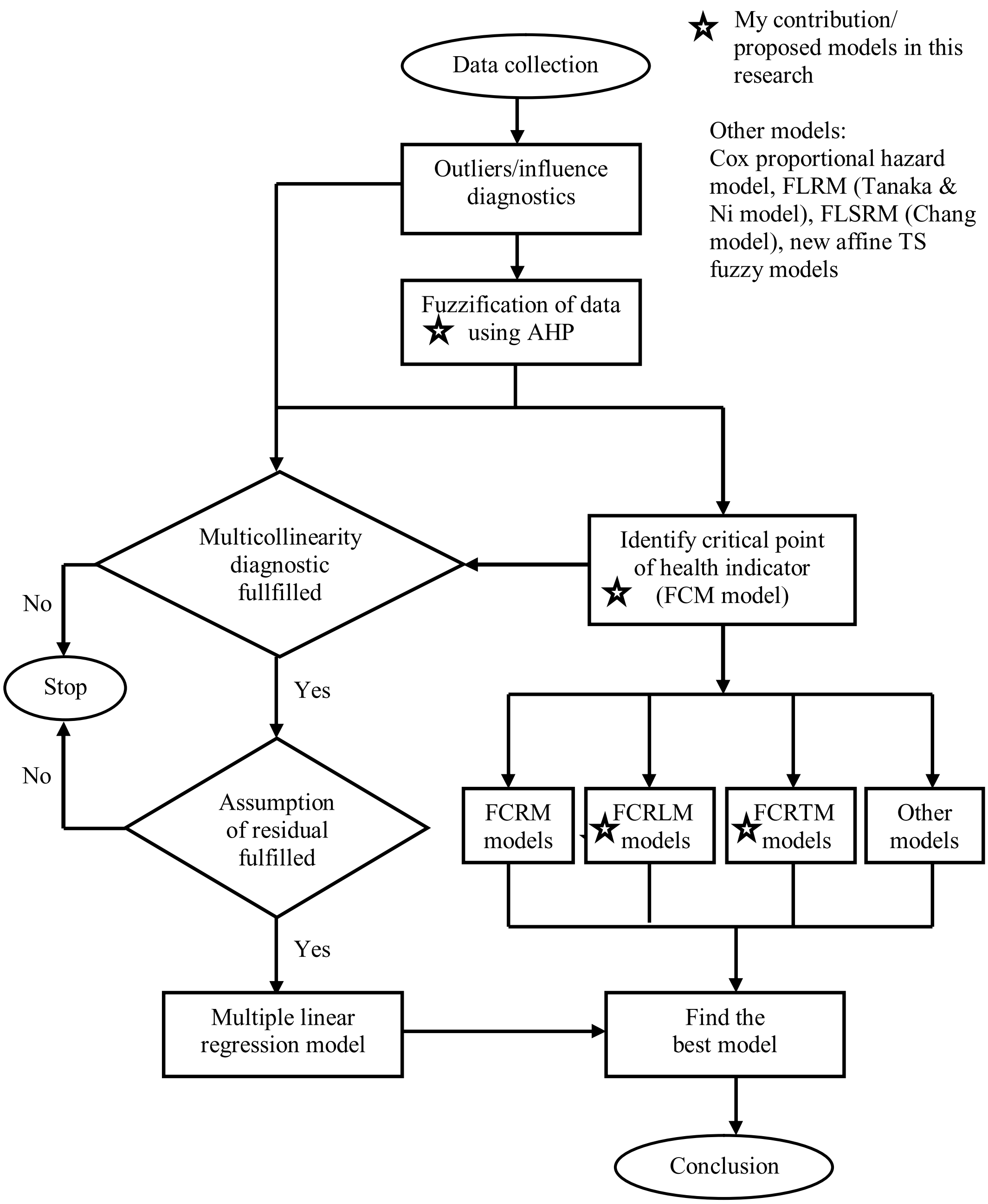

Figure 1.1 Flow chart of research framework

Eight Cases of Data Based on MLR and FCRM Models

Based on MLR model	Based on FCRM models
Original data(without data modification)	Original data(without data modification)
☆ AHP1	☆ AHP1
AHP2	AHP2
FCM model	FCM model
AHP1 + AHP2	AHP1 + AHP2
AHP1 + FCM model	AHP1 + FCM model
AHP2 + FCM model	AHP2 + FCM model
AHP1 + AHP2 + FCM model	AHP1 + AHP2 + FCM model

☆ **Best Modified Data**

Data modification using 3 methods :
AHP1 (AHP technique toward organ failure variable)
AHP2 (AHP technique toward comorbid variable)
FCM (FCM model toward s2sadm variable)

Eleven Models Using the Best Modified Data

MLR + LQD	FCRM (Kung & Lin models)
MLR + truncated error	FCRM (Hathaway & Bezdek models)
Cox proportional hazard model	New affine TS fuzzy models
FLRM (Tanaka model)	☆ FCRTM models
FLRM (Ni model)	FCRLM models
FLSRM (Chang model)	

☆ **Best Models**

Figure 1.2 Eight cases of data and eleven models using the best modified data

1.6 The Scope of The Study

The scope of the study will be divided into two subsections. The first section discusses the scope of the data and followed by a discussion on the scope for the model.

1.6.1 Data Scope

In this research, the data were obtained from the intensive care unit (ICU) of a general hospital in Johor. The data collected by nurses were classified using cluster sampling. It involves 1314 patients in the ICU from 1st January, 2001 to 25th August, 2002. The dependent variable is the patients' status with 0 and 1 codes are used where 0 is coded for patients who are alive in the hospital or the ICU, whereas 1 is coded for patients who died in the hospital or the ICU. There are seven independent variables i.e. sex, race, organ failures (orgfail), comorbid diseases (comorbid), mechanical ventilator (mecvent), score of SAPS II admit (s2sadm) and score of SAPS II discharge from hospital (s2sdisc).

In this thesis, we excluded the patients' status from the dependent variable since the fuzzy clustering for binary data cannot be used. The s2sdisc score is 15 accumulated values for heart rate, blood pressure, age, body temperature, oxygen pressure, urine result, urea serum level, white blood count, potassium serum level, sodium serum level, bicarbonate serum level, bilirubin level, glasgow coma score, chronic illness and type of admittance that have been proposed by Le Gall in 1993. The level of health or health indicator in hospital is measured by the score of s2sdisc. Then, s2sdisc variable is taken as the dependent variable since the s2sdisc and patients' status are determined at the same time. In fact, the highest correlation among independent variables and patients' status is between the patients' status and s2sdisc.

Table 1.1 : An explanation of the dependent and independent variables

No.	Variable Name	Variable Type	Note
1	sex	Qualitative binary with 1= 'Female' and 2= 'Male'	Gender of the patient
2	Race	Qualitative category with 1= 'Malay', 2= 'Chinese', 3= 'Indian', 4= 'Orang Asli, Sabah & Sarawak Indigenous, citizen abroad etc.'	Race of the patient
3	orgfail	Qualitative binary with 1= No organ failure 2= At least one organ failure	Organ failure before and during treatment in the ICU
4	comorbid	Qualitative binary with 1= Did not suffer from comorbid disease, 2= Suffer at least one comorbid disease	Comorbid diseases (existing diseases) before being treated in the ICU
5	mecvent	Qualitative binary with 1= Patients do not use ventilator machine, 2= Patients use ventilator machine	Patients using ventilator machine
6	s2sadm	Quantitative discrete with minimum value of 0	SAPS II score during the first 24 hours in the wards (SAPS II score admit)
7	s2sdisc	Quantitative discrete with minimum value of 0	SAPS II score during the discharge from the ward/hospital (SAPS II score discharge)

1.6.2 Model Scope

Firstly, the analysis of influential and outlier in multiple linear regression (MLR) model should be carried out to the data in order to discard the data due to the assignable causes (human error, machine error and environment error). In this study, we will also use the data mining technique, that is, analytical hierarchy process (AHP) in order to fuzzify the binary data of comorbid disease and organ failure. This technique will transform the binary data to the continuous data within interval [0,1] which is expected to be more accurate and near to the real situation (Rao, 2006).

Then, the fuzzy c-means (FCM) model will be used for s2sadm variable since the variable varies from 0 to 126. This technique will determine the best cluster for this variable as FCM develops hyper-spherical-shaped clusters. In this technique, we will identify the critical point for health indicator. It is important to cluster the patients into “high risk” and “non-high risk”. A medical decision in ICU will be suggested in order to treat intensively high risk patient first. This decision is important to save the life of patients and decrease the mortality rate.

In this study, there are eight cases of data considered as a result of using AHP technique and FCM model toward independent data. Eight cases involving six independent variables with different combination of variable types in each case were considered in order to find the best modified data using MLR and FCRM models. The variables involved are sex (x_1 is binary), race (x_2 is category), orgfail (x_3 is binary or continuous), comorbid (x_4 is binary or continuous), mecvent (x_5 is binary) and s2sadm (x_6 is binary or continuous). Case 4 in the Section 6.2.1 is the beginning data without any modification toward data.

After that, other models will be applied to the best modified data such as multiple linear regression (MLR) model, MLR model with LQD technique, MLR with truncated error, Cox proportional hazard model, fuzzy linear regression model or FLRM (Tanaka and Ni model), fuzzy least squares regression model or FLSRM (Chang model), fuzzy c-regression models or FCRM (Hathaway & Bezdek and Kung & Lin model) and new affine TS fuzzy models. We also proposed new models which are fuzzy c-regression truncated models (FCRTM) and fuzzy c-regression LQD models (FCRLM).

The comparison among other models with FCRTM and FCRLM models will be carried out including its assumption, function of model and the mean square error (MSE). The model with the lowest MSE will be chosen as the best model. The search of the best model is important in order to get the approximation of solution which is closer to the exact solution for the health indicator.

1.7 Research Contributions

There are many benefits that can be gained from this study which can contribute immensely, mainly to the hospital ICU. The contributions can be stated as follows;

(i). The application of data mining technique that is analytic hierarchy process (AHP) in order to fuzzify the binary data so that more accurate prediction can be obtained.

(ii). The suggestion of critical point of health indicator using fuzzy c-means (FCM) model which could be classified as a high risk patient. The making of medical decision in ICU can be more reliable since high-risk patients should be treated first.

(iii). The application of multiple linear regression (MLR) model, Cox proportional hazard model, fuzzy linear regression model (FLRM), fuzzy least squares regression model (FLSRM), fuzzy c-regression models (FCRM), new affine Takagi Sugeno fuzzy models, fuzzy c-regression truncated models (FCRTM) and fuzzy c-regression LQD models (FCRLM) for the health indicator in the ICU.

(iv). The recommendation based on the better model in achieving better services in the ICU, be applied not only in Malaysia but also in other countries.

1.8 Research Importance

Kao (1974) suggested a medical decision in the ICU field by applying the motto "Treating High-risk Patients First". However, he did not use this motto in his study. In this study, we propose the health indicator of patients to be based on their value of SAPS II of discharge (s2sdisc). The value of s2sdisc could be predicted by FCRTM and FCRLM models based on the value of independent variables.

The patients admitted to the ICU are those who come from areas outside the hospital or from within the hospital itself. Since there are many patients admitted to the ICU, the difficulty is to apply the motto "Treating High-risk Patients First". In order to identify the high-risk patients, each patient should have a calculated indicator of their level of health. The patients with high value level of health indicator or classified as high risk patients should be treated immediately and aggressively. This is the importance of the medical decision made in the ICU in order to save the lives of patients with critical conditions. This decision is important to the ICU management in order to decrease mortality rate. As a result, the quality management in ICUs could be improved by decreasing the mortality rate. Additionally, this medical decision making process has not been applied in ICU of any hospitals in this world.

Chapter 2 indicates that many methods used in the ICU involve MLR model and logistic regression model. The fuzzy models are still not a common method used in the ICU. Only Pilz and Engelmann (1998) did a basic fuzzy rule which is given by physician to determine the medical decision made in the ICU. For example, the five conditions of mean arterial pressure (MAP) were determined by 25 fuzzy rules which are the combination of heart rate (very high, high, normal, low and very low) and blood pressure (very high, high, normal, low and very low) which could give a confusing decision. However they did not use FCM and FCRM models to analyze their data. Taking the idea of their work in the field of ICU may give this study a challenge. Since the FCM, FCRM, FCRTM and FCRLM models have not yet been explored in the ICU, we propose the use of these models in the ICU study. The dependent variable used is s2sdisc or health indicator which corresponds and has high correlation with mortality rate. In addition, there are not many rules used in this modelling.

Takrouri (2004) made a medical decision in the ICU. He organized ICUs that cared more for seriously ill patients. This has raised ethical and professional issues related to some patients who had untreatable medical conditions or those who sustained unsalvageable damage to their vital organs. However, he did not use any logistic regression or fuzzy model in his research. The determination of the patients' state of health becomes crucial when there are too many patients who need to be admitted to the ICU and there is insufficient space in the ICU. In fact the application of certain method is still needed in ICU's management.

In order to improve the models, we use the data mining technique that is, AHP technique to fuzzify the binary data of comorbid diseases and organ failures. This technique will transform the binary data to a continuous data within [0,1] interval which is expected to be more accurate and near to the real situation. In fact, this technique is a new technique in analyzing data obtained from ICU.

In FCRM models, there are two important factors, namely the fuzzy model (fuzzification and defuzzification) and the MLR model. Both factors are closely associated in producing the final FCRM models. In this case, the MLR model used in FCRM models is the basic model without considering the problem of outlier data. So, FCRM models common issue is that it is vulnerable to outlier data. In any statistical studies, researchers want to find the latest methods in minimizing the errors.

Several current methods of addressing outlier in the MLR model can be adapted in FCRM models such as least median squares (LMS), least trimmed squares (LTS), deepest regression and least quartile difference (LQD) method. Because of this reason, the new FCRTM and FCRLM models are proposed in this thesis which are robust against outlier. FCRLM models are based on the existing LQD techniques while FCRTM models are based on new ideas about the percentage of contaminated data in the breakdown point. However, FCRTM models show better model in modelling health indicator in the ICU. A significant advantage in the use of fuzzy model is that it can be used for all data types without the need for early assumptions. However, the disadvantage for multiple linear regression model is the residuals should be first fulfill the assumption of normality.

1.9.1 Thesis Organisation

This thesis contains eight chapters. Chapter 1 is the introduction to the thesis. This chapter gives an introduction to the research background, history of ICU, problem description, research objectives, research scopes, research contribution, research importance and a thesis organization.

Chapter 2 is the literature review that contains a discussion on the current and past research on medical field especially in the ICU. The applications of fuzzy modelling are also presented in several fields such as science, medicine, engineering, computer, economics, management and so on. Previous studies on FCRM models are also presented.

In Chapter 3, a detailed explanation of the nine models/technique used in this thesis is presented. The models/technique discussed are multiple linear regression (MLR) model, analytical hierarchy process (AHP) technique, fuzzy c-means (FCM) model, fuzzy c-regression models (FCRM), fuzzy linear regression model (FLRM), fuzzy least squares regression model (FLSRM), new affine Takagi Sugeno fuzzy models, fuzzy c-regression truncated models (FCRTM) and fuzzy c-regression LQD models (FCRLM).

Chapter 4 will discuss the analysis of the proposed model, fuzzy c-regression truncated model (FCRTM) using simulated data. The simulated data are created using S-Plus program. The simulated data consist of one dependent variable and four independent variables. This chapter is important to make sure that simulated data are suitable for the evaluation of the proposed models. Indeed, the proposed model comprises 5 procedures whereby all the procedures need to be fulfilled to validate the potentiality of the proposed model.

The discussion of data background and development of data mining technique (analytic hierarchy process or AHP), fuzzy c-means (FCM) model and multiple linear regression (MLR) model will be presented in Chapter 5. Here, the binary data of comorbid diseases and organ failures will be fuzzified into the continuous data with [0, 1] interval. The different types of comorbid diseases or organ failures will be weighted based on their importance. AHP technique is predicted to get the higher accuracy of prediction. The FCM model will be used to identify the critical point of health indicator.

In Chapter 6, the development of the newly proposed model that are fuzzy c-regression truncated models (FCRTM) and fuzzy c-regression LQD models (FCRLM) will be discussed. Both models are models resulting from the modification of FCRM models. It has five procedures to be followed. The difference of these two models is in the fifth procedure. FCRTM models using truncated residual method, while FCRLM models using the least quartile difference (LQD) technique. In the first procedure, eight cases of data are considered for FCRM models. It includes the original data for the six dependent variables and modified data for the orgfail, comorbid and s2sadm variables of a binary and continuous data using AHP and FCM model.

Chapter 7 discusses the analysis of other models such as multiple linear regression (MLR) model, MLR model with LQD technique, MLR model with truncated residual technique, Cox proportional hazards model, fuzzy linear regression model 1 (Tanaka model), fuzzy linear regression model 2 (Ni model), fuzzy least squares regression model (Chang model), fuzzy c-regression models 1 (Hathaway & Bezdek model), fuzzy c-regression models 2 (Kung & Lin model) and new affine Takagi Sugeno fuzzy models. The overall comparisons among other models with the FCRTM and FCRLM models are discussed to show the reliable and potential of FCRTM and FCRLM models.

Chapter 8 concludes and summarizes the study of the modelling of health indicator in the ICU and then discusses some important results and findings. The best model which has the lowest MSE value will be revealed. Recommendations on areas related to the findings and possible directions for future research in modelling health indicator in the ICU are also presented here.

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