UNIVERSITI PUTRA MALAYSIA

# *FUZZY MEMBERSHIP FUNCTION AND INFERENCE-BASED MODEL FOR PREDICTING STUDENT'S KNOWLEDGE PERFORMANCE*

SALISU MUHAMMAD SANI

FSKTM 2016 6

**FUZZY MEMBERSHIP FUNCTION AND INFERENCE-BASED MODEL FOR PREDICTING STUDENT'S KNOWLEDGE PERFORMANCE**

© COPYRIGHT UPM

**By**

**SALISU MUHAMMAD SANI**

**Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfillment of the Requirements for the Degree of Doctor of Philosophy**

**May 2016**

**COPYRIGHT**

All material contained within the thesis, including without limitation text, logos, icons, photographs and all other artwork, is copyright material of Universiti Putra Malaysia unless otherwise stated. Use may be made of any material contained within the thesis for non-commercial purposes from the copyright holder. Commercial use of material may only be made with the express, prior, written permission of Universiti Putra Malaysia.

Copyright © Universiti Putra Malaysia

© COPYRIGHT UPM

This thesis is dedicated to my family

© COPYRIGHT UPM

Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfillment of the requirement for the degree of Doctor of Philosophy

**FUZZY MEMBERSHIP FUNCTION AND INFERENCE-BASED MODEL FOR PREDICTING STUDENT'S KNOWLEDGE PERFORMANCE**

By

**SALISU MUHAMMAD SANI**

**May 2016**

**Chairman : Teh Noranis Mohd Aris, PhD**
**Faculty : Computer Science and Information Technology**

Intelligent Tutoring Systems (ITSs) are special classes of E-learning systems designed to provide adaptive and personalized tutoring based on the individuality of students. The student model is an important component of an ITS that provides the base for this personalization. During the course of interaction between student and the system, a quantitative representation of the actual student's characteristics such as the student's knowledge state is created based on the observations and predictions the ITS made on each student. The student's knowledge is one of the most dynamic characteristic of the student; so dynamic like a moving target. However, modeling student's knowledge and diagnosis are complex processes that are characterized by uncertainty and imprecision issues that affect the prediction of the student model. Fuzzy logic is a form of multi-valued logic derived from fuzzy set theory. Its methodology provides a definitive solution to problems of information that may be construed as uncertain or imprecise.

A major gap in the existing approach is the absence of an important component of a fuzzy logic controller, the membership function graph which is vital for the management of uncertainty and imprecision in student's knowledge modeling. Moreover, the prediction accuracies of 36% and 90% achieved by the existing models is seen as another limitations in their performance. This study propose novel fuzzy based membership functions and inference mechanisms to design a fuzzy logic based control process which aimed at modeling student's knowledge performance and further diagnosis. Successful design of this two vital fuzzy logic engines will respectively enables the realization of more accurate fuzzy student models and the necessary diagnosis on them. An approximate student model based on fuzzy membership function approach enables making accurate predictions about the state of student's knowledge. The main idea of proposing a novel fuzzy inference process is to provides the necessary diagnosis on the propose fuzzy student model. The inference process take outputs of a fuzzification process with membership functions as input variables for a mechanism which is defined by fuzzy If-Then rules and

© COPYRIGHT UPM

logical operators, and then reaches the output space that produces a human like decision by inferring on the propose fuzzy student models.

For the purpose of this research, the training data which is an instance of students knowledge test performances were obtained from an adaptive-courseware E-learning system that administered knowledge tests to thirty, first year undergraduate students, from two southeastern European Universities, University of split Croatia and University of Mostar Bosnia-Herzegovina in the domain of “computer as a system” comprising of seventy three domain concepts. The results of this knowledge test, the students’ scores in each of the seventy three domain concepts is to be used as crisp inputs to the proposed fuzzy membership functions to enables the realization of the first fuzzy logic control process, the fuzzification process. The propose membership functions are designed using multi fuzzy terms "poor", "weak", "average", "good", "very good" and "excellent" to allow for adequate fuzzy sets that can capture all intervals in the distribution.

However, we need to compare the performance of the propose model with that of the two previous or existing models. With the first model that has 36% accuracy, this comparison is direct as it was implemented using same training data with the propose model. But with second model that has 90% accuracy, this comparison cannot be made directly as it was implemented using different training data with the propose model. This study therefore re-implement the second model using the training data from the domain of “computer as a system” in order to justify the performance of the propose model. The result has shown that the propose method has successfully improved the accuracies of the two previous models.

© COPYRIGHT UPM

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

**FUNGSI KEAHLIAN KABUR DAN MODEL BERDASARKAN KESIMPULAN UNTUK MERAMAL PRESTASI PENGETAHUAN PELAJAR**

Oleh

**SALISU MUHAMMAD SANI**

**Mei 2016**

**Pengerusi : Teh Noranis Mohd Aris, PhD**
**Fakulti : Sains Komputer dan Teknologi Maklumat**

Sistem Tutor Pintar (ITS) adalah kelas khas sistem E-pembelajaran yang direka bentuk untuk memberi tunjuk ajar dan penyesuaian peribadi berdasarkan keperibadian pelajar. Model pelajar adalah salah satu komponen penting di dalam ITS yang menyediakan asas untuk tunjuk ajar peribadi ini. Sepanjang interaksi antara pelajar dan sistem, satu perwakilan kuantitatif ciri-ciri pelajar yang sebenar seperti tahap pengetahuan pelajar dicipta berdasarkan pemerhatian dan ramalan oleh ITS dibuat pada setiap pelajar. Pengetahuan pelajar adalah salah satu sifat yang paling dinamik bagi pelajar; ia begitu dinamik seperti sasaran yang bergerak. Walau bagaimanapun, pemodelan pengetahuan dan diagnosis pelajar adalah proses yang kompleks yang dicirikan oleh isu-isu yang tidak menentu dan ketakpersisan yang memberi kesan kepada ketepatan ramalan model pelajar. Logik kabur adalah salah satu bentuk logik pelbagai-nilai yang diperoleh daripada set teori kabur. Kaedah ini menyediakan penyelesaian muktamad untuk masalah maklumat yang ditafsirkan sebagai tidak menentu atau tidak tepat.

Jurang utama dalam pendekatan yang sedia ada ialah ketiadaan satu komponen penting dalam pengawal logik kabur, keanggotaan graf fungsi yang penting bagi pengurusan data yang tidak menentu dan ketakpersisan dalam pemodelan pengetahuan pelajar. Selain itu, ketepatan ramalan sebanyak 36% dan 90% yang dicapai oleh model sedia ada juga dilihat sebagai satu lagi kekurangan dalam prestasi mereka. Kajian ini mencadangkan satu fungsi kabur berdasarkan keahlian dan mekanisme kesimpulan untuk mereka bentuk satu proses kawalan berasaskan logik kabur yang bertujuan untuk memodel prestasi pengetahuan pelajar dan diagnosis lanjut. Kejayaan reka bentuk bagi kedua-dua enjin logik kabur ini akan membolehkan model pelajar kabur yang lebih tepat dan diagnosis yang diperlukan oleh mereka dapat direalisasikan. Satu model pelajar anggaran berdasarkan pendekatan fungsi keahlian kabur membolehkan ramalan mengenai tahap pengetahuan pelajar dapat dibuat dengan tepat. Idea utama untuk mencadangkan proses kesimpulan kabur yang baru adalah untuk menyediakan diagnosis yang



© COPYRIGHT UPM

diperlukan oleh model pelajar kabur. Proses kesimpulan ini mengambil output daripada proses *fuzzification* bersama fungsi keahlian sebagai pemboleh ubah input untuk mekanisma yang ditakrifkan oleh peraturan Jika-Maka dan pengendali logik, dan kemudian mencapai ruang output yang menghasilkan keputusan seperti yang dibuat oleh manusia dengan membuat kesimpulan berdasarkan kepada model pelajar kabur.

Bagi tujuan kajian ini, data latihan yang merupakan satu contoh persembahan ujian pengetahuan pelajar diperoleh daripada sistem E-pembelajaran adaptif - kursus yang ditadbir ujian pengetahuan kepada tiga puluh pelajar tahun pertama dari dua Universiti Eropah tenggara, Universiti berpecah Croatia dan Universiti Mostar Bosnia-Herzegovina dalam domain "komputer sebagai sistem" yang terdiri daripada tujuh puluh tiga konsep domain. Keputusan bagi ujian pengetahuan ini, skor pelajar dalam setiap satu daripada tujuh puluh tiga konsep domain akan digunakan sebagai input segar dengan fungsi keahlian kabur yang dicadangkan untuk membolehkan proses kawalan logik kabur yang pertama direalisasikan, iaitu proses *fuzzification*. Fungsi keahlian yang dicadangkan direka bentuk menggunakan istilah multi kabur iaitu "miskin", "lemah", "purata", "baik", "sangat baik" dan "cemerlang" bagi membolehkan set kabur yang mencukupi yang boleh menangkap semua selang dalam pengagihan.

Walau bagaimanapun, kita perlu membandingkan prestasi model yang dicadangkan dengan kedua-dua model sebelumnya atau model yang sedia ada. Dengan model pertama yang mencapai 36% ketepatan, perbandingan ini adalah secara langsung kerana ia telah dilaksanakan dengan menggunakan data latihan yang sama dengan model yang dicadangkan. Tetapi dengan model kedua yang mencapai 90% ketepatan , perbandingan ini tidak boleh dibuat secara terus kerana ia telah dilaksanakan dengan menggunakan data latihan yang berbeza dengan model yang dicadangkan. Oleh itu, kajian ini telah melaksanakan semula model kedua menggunakan data latihan daripada domain "komputer sebagai satu sistem" untuk membuat justifikasi prestasi model yang dicadangkan. Hasil kajian menunjukkan bahawa kaedah yang dicadangkan ini telah berjaya meningkatkan ketepatan kedua-dua model sebelumnya.

© COPYRIGHT UPM

## ACKNOWLEDGEMENTS

First of all, I would like to extend my sincere gratitude to my supervisor, Dr Teh Noranis Mohd Aris for her advice and guidance throughout the entire period of my study. It was invaluable.

I would also like to thank my co-supervisors, Dr Norwati Mustapha and Dr MD Nasir Sulaiman for their innumerable assistance and guidance.

I need also to acknowledge the effort of my sponsors, the tertiary education trust fund (TETFUND NIGERIA), the Jigawa State Government, the entire management of my institution, Jigawa State Polytechnic, in particular the Rector, Professor G.U Goje who has been a role model and an inspiration.

I would like to express my sincere appreciation to Professor Ani Grubišić, University of Split Croatia for providing me with the experimental data that was vital for the smooth implementation of my work.

My profound gratitude to Alhaji Muhammad Babiye and his wife Hajiya Jamila Abba for their support and guidance.

I remain grateful to all the members of my family. I really appreciate their love and support.


© COPYRIGHT UPM

I certify that a Thesis Examination Committee has met on 25 May 2016 to conduct the final examination of Salisu Muhammad Sani on his thesis entitled "Fuzzy Membership Function and Inference-Based Model for Predicting Student's Knowledge Performance" in accordance with the Universities and University Colleges Act 1971 and the Constitution of the Universiti Putra Malaysia [P.U.(A) 106] 15 March 1998. The Committee recommends that the student be awarded the Doctor of Philosophy.

Members of the Thesis Examination Committee were as follows:

**Abu Bakar bin Md Sultan, PhD**
Professor
Faculty of Computer Science and Information Technology
Universiti Putra Malaysia
(Chairman)

**Razali bin Yaakob, PhD**
Associate Professor
Faculty of Computer Science and Information Technology
Universiti Putra Malaysia
(Internal Examiner)

**Marzanah binti A. Jabar, PhD**
Associate Professor
Faculty of Computer Science and Information Technology
Universiti Putra Malaysia
(Internal Examiner)

**David Al-Dabass, PhD**
Professor Emeritus
Nottingham University
United Kingdom
(External Examiner)

**ZULKARNAIN ZAINAL, PhD**
Professor and Deputy Dean
School of Graduate Studies
Universiti Putra Malaysia

Date: 23 August 2016

This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Doctor of Philosophy. The members of the Supervisory Committee were as follows:

**Teh Noranis Mohd Aris, PhD**
Senior Lecturer
Faculty of Computer Science and Information Technology
Universiti Putra Malaysia
(Chairman)

**Norwati Mustapha, PhD**
Associate Professor
Faculty of Computer Science and Information Technology
Universiti Putra Malaysia
(Member)

**MD Nasir Sulaiman, PhD**
Associate Professor
Faculty of Computer Science and Information Technology
Universiti Putra Malaysia
(Member)

**BUJANG BIN KIM HUAT, PhD**
Professor and Dean
School of Graduate Studies
Universiti Putra Malaysia

Date:

© COPYRIGHT UPM

**Declaration by graduate student**

I hereby confirm that:

- this thesis is my original work;
- quotations, illustrations and citations have been duly referenced;
- this thesis has not been submitted previously or concurrently for any other degree at any other institutions;
- intellectual property from the thesis and copyright of thesis are fully-owned by Universiti Putra Malaysia, as according to the Universiti Putra Malaysia (Research) Rules 2012;
- written permission must be obtained from supervisor and the office of Deputy Vice-Chancellor (Research and Innovation) before thesis is published (in the form of written, printed or in electronic form) including books, journals, modules, proceedings, popular writings, seminar papers, manuscripts, posters, reports, lecture notes, learning modules or any other materials as stated in the Universiti Putra Malaysia (Research) Rules 2012;
- There is no plagiarism or data falsification/fabrication in the thesis, and scholarly integrity is upheld as according to the Universiti Putra Malaysia (Graduate Studies) Rules 2003 (Revision 2012-2013) and the Universiti Putra Malaysia (Research) Rules 2012. The thesis has undergone plagiarism detection software.

Signature: ________________________ Date: __________________

Name and Matric No.: Salisu Muhammad Sani, GS34912

© COPYRIGHT UPM

**Declaration by Members of Supervisory Committee**

This is to confirm that:

- the research conducted and the writing of this thesis was under our supervision;
- Supervision responsibilities as stated in the Universiti Putra Malaysia (Graduate Studies) Rules 2003 (Revision 2012-2013) are adhered to.

Signature: ______________________________
Name of Chairman of Supervisory Committee: Dr. Teh Noranis Mohd Aris

Signature: ______________________________
Name of Member of Supervisory Committee: Associate Professor Dr. Norwati Mustapha

Signature: ______________________________
Name of Member of Supervisory Committee: Associate Professor Dr. MD Nasir Sulaiman

© COPYRIGHT UPM

## TABLE OF CONTENTS



© COPYRIGHT UPM

© COPYRIGHT UPM

© COPYRIGHT UPM

## LIST OF TABLES



© COPYRIGHT UPM

## LIST OF FIGURES



© COPYRIGHT UPM

## LIST OF EQUATIONS



© COPYRIGHT UPM

# LIST OF ABBREVIATIONS

| | |
|---|---|
| ITS : | Intelligent Tutoring System |
| AI : | Artificial Intelligence |
| ICT : | Information and Communication Technology |
| DSI : | Domain Specific Information |
| CBM : | Constrain-Based Modeling |
| DKG : | Domain Knowledge Graph |
| DM: | Differential Model |
| BKT: | Bayesian Knowledge Tracing |
| FSM: | Fuzzy Student Model |
| S(A): | Support of a Fuzzy Set |
| C(A): | Core of a Fuzzy Set |
| Hgt(A): | Height of a Fuzzy Set |
| Max: | Maximum |
| Min: | Minimum |
| Freq: | Frequency |
| $P_{mat}$: | Numnber of Prediction Match |
| $P_{ind}$: | Number of Prediction Indication |
| Pmis: | Number of Prediction Miss |

© COPYRIGHT UPM

## LIST OF SYMBOLS

| | |
|---|---|
| $\mu(x)$ | membership degree |
| $\alpha$ | alpha cut |
| $\cup$ | union symbol |
| $\cap$ | intersection symbol |
| K | domain concept |
| F | function of score value |
| $\bar{A}$ | fuzzy compliment |
| $\lambda$ | constant notation |
| $\delta$ | prediction parameter |
| $f_T$ | fuzzy term |

© COPYRIGHT UPM

# CHAPTER 1

# INTRODUCTION

## 1.1 Background and Motivation

Intelligent Tutoring Systems (ITSs) are computer based educational systems designed to provide customized instruction and immediate feedback to students, without the intervention of human beings. For over four decades since their inception, these systems keep growing more sophisticated with increasingly large influence in education. Originally, the intention of designing and developing such systems was due to the vision that Artificial Intelligence (AI) could produce a promising solution to the limitations educational professionals were facing: how to effectively teach and help students learn in a large scale (Nkambou, Bordeau, & Mizoguchi, 2013).

It has been established that the effectiveness of teaching and learning activities improve when the ratio of student-to-teacher become smaller. In 1984, Bloom conducted experiments comparing student learning under conditions, a 30 students per teacher class on one side and one-to-one tutoring on the other, and found that the one-to-one tutoring is much more effective than the group teaching (Bloom, 1984). On one hand, the need to achieve high students' ratios in learning environments regardless of time and location and without requiring an impractical number of expert human tutors became increasingly pragmatic. On the other hand, AI researchers were keenly seeking a meaningful venue for their enthusiasms to spread the power of AI in many traditional fields at the time when AI was blossoming. Computer scientists, cognitive scientists, educational professionals viewed the newborn ITS paradigm as a means to fulfill their various goals. ITSs use AI techniques to help students learn with little or no human intervention. An ITS therefore is viewed as a multi-disciplinary area of research that requires seamless collaborations of a variety of disciplines, such as education, cognitive science, learning science, and computer science.

The ability to provide immediate feedback and individualized assistance by this computer-based educational paradigm is achieved through collaboration by four major components of the system; domain model, tutor model, student model and the user interface (Conati & Kardan, 2013). Domain modeling is a technique to encode domain knowledge, such as concepts, rules and procedures, facilitating their use in computer systems. This part of the system is often called expert knowledge, and systems focusing more on domain modeling are called expert systems. Student modeling is a technique used to understand students, including their knowledge level, behaviors and emotions; this model provides computer-interpretable representations of the actual student to the system. The tutoring model consumes the knowledge from the domain model and the student model. It directs the system to provide human-like tutoring with applications of several different pedagogical strategies. For example, given the estimation of student misconception, the output of the student model, comparing it with the domain knowledge, the output of the domain model,



© COPYRIGHT UPM

the tutor model may decide what tutorial actions are necessary to conduct. If an intervention decision has to be made, the tutor model is responsible for making a wise decision as to when and how to intervene. Finally, all these three models collaborate as services at backend and the user interface works as a presentational tier to blend the services together to interact and communicate with the user.

## 1.2 Student Modeling

Student modeling is a vital process in ITS where the tutoring system observe student's actions and creates a quantitative representations of student properties of interest, which are vital to other, ITS modules (Priya & Keerthy, 2015). The main goal of a student model is to support making instructional decisions based on the individuality of the learners. A good student model that matches student behaviors to student properties of interest can often provide insightful information to both the system and the researchers. Student behaviors can be viewed as the input of a student model, which include a variety of observations, such as student responses and actions. Student's characteristics of interest represent what the student is being modeled.

Depending on the requirements, the range of things being modeled could be fairly broad: student knowledge, student performance, student emotion and other constructs of interest. Student models create quantitative representations, which are consumable to other modules within the ITS, and most of which are also interpretable to humans outside the system. It has been said that a well-designed tutoring system actively undertakes two tasks: that of the diagnostician, discovering the nature and extent of the student's knowledge, and that of the strategist, planning a response using its findings about the learner (Jeremić, Jovanović, & Gašević, 2012). This is the main role of student model, which is the base for personalization in intelligent tutoring systems (Conati, 2010). The information of a student model is used by the system in order to adapt its responses to each individual student dynamically providing personalized instruction, help and feedback. The student model is used for accurate diagnosis in order to predict students' needs and adapt the learning materials and processes to each individual student's learning pace. It is used to produce highly accurate estimations of the student's knowledge level and cognitive state in order to deliver the most appropriate learning materials to the students.

Furthermore, an adaptive or personalized tutoring system can consult the student model in order to recognize the learning style and preferences of a student and make a decision about the learning strategy that is likely to be the most effective for each student. Moreover, by predicting of student affective state, an adaptive and/or personalized educational system can select appropriate learning methods in order to increase the effectiveness of tutorial interactions and improve the learning and motivation. In addition, a student model can be used for identifying the student's strength and weaknesses in order to provide him/her with customized or individualized feedback (Chrysafiadi & Virvou, 2013).

© COPYRIGHT UPM

The student's knowledge is one of the most dynamic characteristic of the student; so dynamic like a moving target. The task of expressing student knowledge level is confronted with high degree of uncertainty, imprecision and human subjectivity. This changing attribute in student's knowledge state accounts for the complexity in its modeling. One approach for dealing with these issues of imprecision is the use of fuzzy logic technique which has similar way of expressing the natural human conceptualization (Chrysafiadi & Virvou, 2012). The student model creates a quantitative representation of a student's dynamic characteristics in numeric form; this information needs to be processed using sharply defined criteria (Grubišić, Stankov, & Žitko, 2014). For this reasons, the need for fuzzy membership functions as tool for simulating fuzziness in human cognition becomes apparent.

## 1.3 Fuzzy logic in Student Modeling

Fuzzy logic systems are rule-based systems that use the theory of fuzzy sets and fuzzy logic introduced by Zadeh (Zadeh, 1965) to encounter imprecision and uncertainty. It deals with reasoning that is approximate rather than fixed and exact. It is a precise logic of imprecision and approximate reasoning. In other words, fuzzy logic is able to reason and make rational decisions in circumstances of imprecision, uncertainty, human subjectivity, incomplete information and deficient computations (Almaraashi, 2012). Many applications are using fuzzy logic systems to represent knowledge in a closer way to how human are thinking. In a fuzzy set, any element in the set is given a degree of membership of this set as opposed to the ordinary crisp set where its membership is characterized by two values only (0 or 1). A general fuzzy logic system involves fuzzifying crisp values followed by inference engine to apply fuzzy rules and ends by defuzzifying the results into crisp values as outputs. The ability of fuzzy logic to handle the uncertainty, imprecise and incomplete data, and information that is characterized by human subjectivity makes it useful in many human-centric fields (Ajiboye, Arshah, & Qin, 2013). Fuzzy set theory has been applied in the design and development of intelligent tutoring systems, more specifically in student model design.

Modeling student's dynamic characteristics like knowledge is not a straightforward task, since it often depends on and is reflected through things that cannot be directly observed and measured (Jeremić et al., 2012). Especially in an intelligent tutoring system, where there is no direct interaction between the teacher and the student, there may be difficulties and problems in handling information about students' cognitive state and behavior. The tutoring system needs to know what knowledge the student has and what goals the student is currently trying to achieve. That means, the system must do both assessment and plan recognition to create a good representation of the student. These are modeling tasks that involve a high level of uncertainty (Vieira, 2015). One possible approaches to encounter this uncertainty and imprecision is fuzzy logic. Fuzzy logic involves the use of natural language in the form of If-Then statements to demonstrate knowledge of domain experts and hence generates decisions and facilitates human-like reasoning based on uncertain and imprecise information coming from the student-computer interaction (Goel, Lallé, & Luengo, 2012). The main advantage of using fuzzy logic is that humans often reason in terms



© COPYRIGHT UPM

of vague concepts when dealing with situations in which they experience uncertainty and imprecision (Wang, 2015). Hence we go for a technique that effectively maps the subjective concepts such as students' knowledge modeling with the help of membership function. Through the use of the membership functions, fuzzy logic is able to handle issues in student's knowledge modeling caused by imprecision and uncertainty (Drigas, Argyri, & Vrettaros, 2009). Membership functions are subjective and context-dependent that means that it is hard for a computer system to automatically generate them in a concrete and formal way. The choice of membership functions is a key problem in the design of a fuzzy controller. The membership functions can take one of the symmetric or asymmetric forms of triangles, exponential Gauss, trapezoid and so on in the general unified form. The roles of membership functions in a fuzzy logic controller is to map a crisp inputs, the numeric values $x \in X$(crisp set) into a fuzzified value, $A \in U$(universe of discourse)(Chrysafiadi & Virvou, 2015).

## 1.4 Research problems

One serious issue facing the existing models is in their performance. The prediction accuracies of 36% and 90% respectively achieved by (Grubišić, Stankov, & Peraić, 2013) and (Danaparamita & Lumban Gaol, 2014) still leave enough room for investigation and improvement.

The absence of an essential component of fuzzy logic controller, the membership functions graph which is vital for the fuzzy approximate reasoning capability to manage the uncertainty and imprecision issues in modeling students' knowledge states has created a gap within the Danaparamita's fuzzy logic approach.

The issue of undefined intervals in Danaparamita's Bayesian distribution is owing to overreliance on only two valued probability density variables known and unknown (true or false). This has created serious limitation in Danaparamita's approach which left all input spaces that falls within those undefined intervals untreated.

The use of dependency graph as fuzzy based inference mechanism adopted by Danaparamita's fuzzy model is more to domain than student model design and that contributed to its low performance of 86.25% accuracy as against the 90% success recorded by the Bayesian model.

© COPYRIGHT UPM

## 1.5 Research objectives

The main goal of this research is to propose fuzzy student’s model with high degree of accuracy to improve the performances of 36% and 90% respectively achieved by Grubišić and Danaparamita's models. Modeling this component will adopt the following ideas:

1. Propose novel fuzzy membership functions that will enable the realization of the fuzzifier component for essential fuzzification process to address the prevailing issues of uncertainty and imprecision with the Danaparamita's fuzzy model through the fuzzy approximate reasoning.
2. Propose multi-valued fuzzy sets based on multi-valued fuzzy variables to capture all intervals in the membership function distributions.
3. Propose novel rule-based fuzzy inference mechanism using fuzzy If-Then rules for the necessary diagnosis to infer on the propose fuzzy models.

## 1.6 Research Scope

The study focuses towards modeling the student component of an ITS and more specifically, modeling of student’s knowledge characteristic and its diagnosis. To achieve these prevailing tasks, the study proposes novel fuzzy membership functions and fuzzy If-Then inference rules to respectively enable the realization of two vital fuzzy logic control processes, the fuzzification and fuzzy inference mechanisms. The training data is from an Adaptive-Courseware Tutor system (Grubiši, 2012) that is defined in the domain of "computer as a system" comprising of seventy three domain knowledge concepts.

## 1.7 Research Contribution

The main contribution of this study is proposing fuzzy logic control approach to model the student component of an ITS. The following are the novel features of the propose technique:

- Propose novel membership functions with multi-valued fuzzy sets to enables making accurate predictions about student's knowledge state
- Propose novel fuzzy If-Then inference rules to enables the necessary diagnosis and evaluation of the proposed fuzzy student model

© COPYRIGHT UPM

## 1.8 Thesis Organization

Chapter two aims at providing review of the related literature. First, the concept of student modeling, the relevant modeling approaches that are used in modeling this key component of an ITS and analysis of the limitations of this approaches as well as those of the existing models. The chapter also provides a comprehensive review of the propose fuzzy logic technique, its architecture and components in order to enables the understanding of how to the framework of the propose model. Chapter three is dedicated to primarily describe the research methodology. The chapter first provide the framework of the research design which includes the conceptual model of the propose fuzzy based student model. In addition, this chapter also explains the materials needed in both software and hardware for achieving the objectives of the research. Chapter four aims at presenting the design of both proposed membership functions, fuzzy student models as well as the rule based inference mechanism. Chapter five aims at presenting results and discussion. Finally, chapter six presented the conclusion and future works.

© COPYRIGHT UPM

## REFERENCES


Ajiboye, A. R., Arshah, R. A., & Qin, H. (2013). Risk Status Prediction and Modelling Of Students ' Academic Achievement - A Fuzzy Logic Approach. International Journal Of Engineering And Science, 3(11), 7–14.

Albano, G. (2012). A knowledge-skill-competencies e-learning model in mathematics. Conocimientos, Destrezas Y Competencias: Un Modelo Para Aprender Matemáticas En Un Entorno Virtual, 9(1), 306–319.

Ali, O. A. M., Ali, A. Y., & Sumait, B. S. (2015). Comparison between the Effects of Different Types of Membership Functions on Fuzzy Logic Controller Performance. International Journal of Emerging Engineering Research and Technology, 3(3), 76–83.

Almaraashi, M. (2012). Learning of Type-2 Fuzzy Logic Systems using Simulated Annealing. PhD Theisis.

Anderson, A. C. and J. R. (1995). Anderson & Sheu, 1995.pdf. Knowledge Tracing: Modeling the Acquisition of Procedural Knowledge, 4, 253–278.

Arroyo, I., Woolf, B. P., Burelson, W., Muldner, K., Rai, D., & Tai, M. (2014). A multimedia adaptive tutoring system for mathematics that addresses cognition, metacognition and affect. International Journal of Artificial Intelligence in Education, 24(4), 387–426.

Baker, R. S. J. D., Corbett, A. T., Gowda, S. M., Wagner, A. Z., MacLaren, B. A., Kauffman, L. R., … Giguere, S. (2010). Contextual slip and prediction of student performance after use of an intelligent tutor. In 18th International Conference, UMAP 2010, Big Island, HI, USA, June 20-24, 2010. Proceedings (Vol. 6075 LNCS, pp. 52–63).

Balakrishnan, A. (2011). Multi-disciplinary Trends in Artificial Intelligence. In Conference: Multi-disciplinary Trends in Artificial Intelligence - 5th International Workshop, MIWAI 2011, Hyderabad, India, December 7-9, 2011.

Barak, M. (2010). Motivating self-regulated learning in technology education. International Journal of Technology and Design Education, 20(4), 381–401.

Baschera, G. M., & Gross, M. (2010). Poisson-based inference for perturbation models in adaptive spelling training. International Journal of Artificial Intelligence in Education, 20(4), 1–31.

Bloom, B. S. (1984). The 2 Sigma Problem: The Search for Methods of Group Instruction as Effective as One-to-one Tutoring, 13(6), 4–16.

Butz, C. J., Hua, S., & Maguire, R. B. (2004). Bits: a Bayesian Intelligent Tutoring System for Computer Programming. In Wccce '04 (pp. 179–186).


© COPYRIGHT UPM

Byungwoon, S. L. and. (2011). Optimal tuning of PI-like fuzzy controller using variable membership function' s slope. In INTECH, 2011 KOREA (pp. 196–207). http://doi.org/10.1109/ISAM.2009.5376964.

Carmona, C., Castillo, G., & Millan, E. (2008). Designing a Dynamic Bayesian Network for Modeling Students' Learning Styles. In 2008 Eighth IEEE International Conference on Advanced Learning Technologies (pp. 346–350). http://doi.org/10.1109/ICALT.2008.116.

Centintas, S. (2010). Automatic Detection of Off-Task Behaviors in Intelligent Tutoring System with Machine Learning Techniques. IEEE Transaction on Learning Technologies, 7, 1–9.

Chi, M., Koedinger, K. R., Gordon, G., Jordan, P. W., & VanLehn, K. (2011). Instructional Factors Analysis: A Cognitive Model For Multiple Instructional Interventions. In Proceedings of the 4th International Conference on Educational Data Mining, Eindhoven, The Netherlands, July 6-8, 2011 (pp. 61–70).

Chrysafiadi, K., & Virvou, M. (2012). Evaluating the integration of fuzzy logic into the student model of a web-based learning environment. Expert Systems with Applications, 39(18), 13127–13134.

Chrysafiadi, K., & Virvou, M. (2013). Student modeling approaches: A literature review for the last decade. Expert Systems with Applications, 40(11), 4715–4729.

Chrysafiadi, K., & Virvou, M. (2015). Fuzzy Logic in Student Modeling. In Intelligent Systems Reference Library (Vol. 78, pp. 25–59).

Conati, C. (2010). Bayesian student modeling. Studies in Computational Intelligence, 308(1), 281–299. http://doi.org/10.1007/978-3-642-14363-2_14.

Conati, C., & Kardan, S. (2013). Student modeling: Supporting personalized instruction, from problem solving to exploratory open-ended activities. AI Magazine, 34(3), 13–26.

Corbett, A., Kauffman, L., Maclaren, B., Wagner, A., & Jones, E. (2010). A Cognitive Tutor for Genetics Problem Solving: Learning Gains and Student Modeling. Journal of Educational Computing Research, 42(2), 219–239.

Danaparamita, M., & Lumban Gaol, F. (2014). Comparing student model accuracy with bayesian network and fuzzy logic in predicting student knowledge level. International Journal of Multimedia and Ubiquitous Engineering, 9(4), 109–120.

Dorça, F. A., Lima, L. V., Fernandes, M. A., & Lopes, C. R. (2012). A Stochastic Approach for Automatic and Dynamic Modeling of Students ' Learning Styles in Adaptive Educational Systems. Informatics in Education, 11(2), 191–212.



© COPYRIGHT UPM

Drigas, A. S., Argyri, K., & Vrettaros, J. (2009). Decade Review (1999-2009): Artificial Intelligence Techniques in Student Modeling. Knowledge, Learning, Development and Technology for All, 49, 552–564.

Dubey, S., Pandey, R. K., & Gautam, S. S. (2014a). Dealing with Uncertainty in Expert Systems. IInternational Journal of Soft Computing and Engineering, 4(3), 105–111.

Dubey, S., Pandey, R. K., & Gautam, S. S. (2014b). Dealing with Uncertainty in Expert Systems. International Journal of Social Science and Humanity, 4(3), 105–111.

Durrani, S., & Durrani, Q. S. (2010). Intelligent Tutoring Systems and cognitive abilities, 12(3), 1–10.

Folsom-Kovarik, J. T., Sukthankar, G., & Schatz, S. (2013). Tractable POMDP representations for intelligent tutoring systems. ACM Transactions on Intelligent Systems and Technology, 4(2), 1–22.

Gaudioso, E., Montero, M., & Hernandez-Del-Olmo, F. (2012). Supporting teachers in adaptive educational systems through predictive models: A proof of concept. Expert Systems with Applications, 39(1), 621–625.

Goel, G., Lallé, S., & Luengo, V. (2012). Fuzzy logic representation for student modelling: Case study on geometry. In 11th International Conference on Intelligent Tutoring Systems, Greece (Vol. 7315 LNCS, pp. 1–6).

Gong, Y. (2014). Student Modeling in Intelligent Tutoring Systems. PhD Thesis

Gong, Y., Beck, J. E., & Heffernan, N. T. (2011). How to construct more accurate student models: Comparing and optimizing knowledge tracing and performance factor analysis. International Journal of Artificial Intelligence in Education, 21(1-2), 27–46.

González-Brenes, J. P. (2015). Modeling Skill Acquisition Over Time with Sequence and Topic Modeling. In Aistats-2015 (Vol. 38, pp. 296–305).

Grubiši, A. (2012). ADAPTIVE STUDENT ' S KNOWLEDGE ACQUISITION MODEL IN E-LEARNING SYSTEMS. PhD Thesis.

Grubiši, A., Stankov, S., & Žitko, B. (2013a). Stereotype Student Model for an Adaptive e- Learning System Stereotype Student Model for an Adaptive e-Learning System. International Journal of Computer, Electrical, Automation, Control and Information Engineering, 7(4), 440–447.

Grubiši, A., Stankov, S., & Žitko, B. (2013b). Stereotype Student Model for an Adaptive e- Learning System Stereotype Student Model for an Adaptive e-Learning System, 7(APRIL), 440–447.



© COPYRIGHT UPM

Grubišić, A., Stankov, S., & Peraić, I. (2013). Ontology based approach to Bayesian student model design. Expert Systems with Applications, 40(13), 5363–5371.

Grubišić, A., Stankov, S., & Žitko, B. (2014). Adaptive courseware model for intelligent e-learning systems. In International Conference on Computing, E-Learning and Emerging Technologies (ICCEET 2014).

Guerra, J., Huang, Y., Hosseini, R., & Brusilovsky, P. (2015). Exploring the Effects of Open Social Student Model Beyond Social Comparison. In AEID 2015 Workshop Proceedings (Vol. 3, pp. 19–24).

Hamdan, H. (2013). An Exploration of the Adaptive Neuro-Fuzzy Inference System ( ANFIS ) in Modelling Survival Thesis submitted to The University of Nottingham for the Degree of Doctor of Philosophy An Exploration of the Adaptive Neuro-Fuzzy Inference System ( ANFIS ) .

Harry Armstrong. (2015). Machines THAT Learn in the Wild.

Iancu, I. (2012). A Mamdani Type Fuzzy Logic Controller. In Fuzzy Logic - Controls, Concepts, Theories and Applications (pp. 325–350).

Inventado, P. S., Legaspi, R., Suarez, M., & Numao, M. (2011). Predicting Student Emotions Resulting From Appraisal of Its Feedback. Research and Practice in Technology Enhanced Learning, 6(2), 107–133.

Jeremić, Z., Jovanović, J., & Gašević, D. (2012). Student modeling and assessment in intelligent tutoring of software patterns. Expert Systems with Applications, 39(1), 210–222.

Jia, B., Zhong, S., Zheng, T., & Liu, Z. (2010). The Study and Design of Adaptive Learning System Based on Fuzzy Set Theory. In Transactions on edutainment IV (pp. 1–11).

Khodeir, N., Wanas, N., & Darwish, N. (2010). U TILIZING D IAGNOSING PROBLEMS IN A P ROBABILISTIC D OMAIN TO B UILD S TUDENT. International Journal of Computer Science & Information Technology, 2(4), 88–97.

Li, N., Cohen, W., Koedinger, K., Matsuda, N., & Mellon, C. (2011). A Machine Learning Approach for Automatic Student Model Discovery. Educational Data Mining, 12, 31–40.

Limongelli, C., Sciarrone, F., & ... (2011). Personalized e-learning in Moodle: the Moodle_LS System. Journal of E-Learning …, 7(1), 49–58.

Loc Nguyen and Phung Do. (2008). Learner model in adaptive learning system. In Fifth World academy of Science, Engineering and Technology (pp. 395–400).

Mahnane, L., Laskri, M. T., & Trigano, P. (2012). An Adaptive Hypermedia System Integrating Thinking Style ( AHS-TS ): Model and Experiment Department of computer science , university of Annaba , Algeria 2 . Thinking Style and Models. International Journal of Hybrid Information Technology, 5(1), 11–28.

Martins, A. C., Faria, L., De Carvalho, C. V., & Carrapatoso, E. (2008). User Modeling in adaptive hypermedia educational systems. Educational Technology Society, 11(1), 194–207.

Mitrovic, a, & Martin, B. (2006). Evaluating the effects of open student models on learning. In Second International Conference on Adaptive Hypermedia and Adaptive Web-Based Systems (pp. 296–305).

Nkambou, R., Bordeau, J., & Mizoguchi, R. (2013). Advances in Intelligent Tutoring Systems. Journal of Chemical Information and Modeling (Vol. 53).

Pardos, Z. A., Baker, R. S. J. D., San Pedro, M. O. C. Z., Gowda, S. M., & Gowda, S. M. (2013). Affective States and State Tests: Investigating How Affect Throughout the School Year Predicts End of Year Learning Outcomes. In Proceedings of the Third International Conference on Learning Analytics and Knowledge - LAK '13 (pp. 117–124).

Penaa, A., Kayashima, M., Mizoguchi, R., & Dominguez, R. (2011). Improving students' meta-cognitive skills within intelligent educational systems: A review. In 6th International ConferenceFoundation of Augmented Cognition (Vol. 6780 LNAI, pp. 442–451).

Peña-Ayala, A., Sossa-Azuela, H., & Cervantes-Pérez, F. (2012). Predictive student model supported by fuzzy-causal knowledge and inference. Expert Systems with Applications, 39(5), 4690–4709.

Piech, C., Spencer, J., Huang, J., Ganguli, S., Sahami, M., Guibas, L., … Academy, K. (2015). Deep Knowledge Tracing. In 28th Conference on Advances in Neural Networks Information Processi (pp. 1–13).

Popescu, E., Bădică, C., & Moraret, L. (2009). WELSA: An intelligent and adaptive web-based educational system. Studies in Computational Intelligence, 237, 175–185.

Priya, M. R., & Keerthy, G. (2015). Rule-Based Fuzzy Logic for Automatic Learning Process in an E-learning Environment, 4(7), 567–571.

Razali, S. Z., Wong, S. V, & Ismail, N. (2011). Fuzzy Logic Modeling For Peripheral End Milling Process. IOP Conference Series: Materials Science and Engineering, 17, 1–11.

© COPYRIGHT UPM

Roll, I., Aleven, V., & Koedinger, K. R. (2010). The invention Lab: Using a hybrid of model tracing and constraint-based modeling to offer intelligent support in inquiry environments. In 10th International Conference, ITS 2010, Pittsburgh, PA, USA, June 14-18, 2010, Proceedings, Part I (Vol. 6094 LNCS, pp. 115–124).

Shahrieel, M., & Ashikin, F. (2011). Study of the Effect in the Output Membership Function When Tuning a Fuzzy Logic Controller. In International Conference on Control Systems, Computing and Engineering (pp. 1–6).

Sleeman, D. (1984). An attempt to understand students' understanding of basic algebra. Cognitive Science, 8(4), 387–412.

Sleeman, D. (1985). Basic algebra revisited: A study with 14-year-olds. International Journal of Man-Machine Studies, 22(2), 127–149.

Somyürek, S. (2009). Student modeling: Recognizing the individual needs of users in e-learning environments. International Journal of Human Sciences, 6, 429.

Turc, C. G., & Belgiu, G. (2013). Fuzzy Logic Applications in Flanges Manufacturing. Advanced Materials Research, 837, 223–227.

VanLehn, K. (2013). Model construction as a learning activity: a design space and review. Interactive Learning Environments, 21(4), 371–413.

Vieira, A. (2015). Predicting online user behaviour using deep learning algorithms. I N Ter N Ational Jour Nal of Com Puter Scien Ce I Ssues, 7(1), 1–21.

Voskoglou, M. (2013). Fuzzy Logic as a Tool for Assessing Students' Knowledge and Skills. Education Sciences, 3(2), 208–221.

Wang, C. (2015). A Study of Membership Functions on Mamdani-Type Fuzzy Inference S. PhD Thesis.

Webb, T. L., Gallo, I. S., Gollwitzer, P. M., & Sheeran, P. (2012). Effective regulation of affect: An action control perspective on emotion regulation. European Review of Social Psychology, 23(1), 143–186.

Yang, G., Kinshuk, & Graf, S. (2010). A practical student model for a location-aware and context-sensitive personalized adaptive learning system. In 2010 International Conference on Technology for Education, T4E 2010 (pp. 130–133).

Yudelson, M. V, Koedinger, K. R., & Gordon, G. J. (2013). Individualized Bayesian Knowledge Tracing Models (pp. 1–9). http://doi.org/10.1007/978-3-642-39112-5-18.

Zadeh, L. A. (1965). Zadeh-1965.pdf. Information and Control, 8, 388–353.



© COPYRIGHT UPM

Zhang, J., & Ghorbani, A. A. (2007). GUMSAWS: A generic user modeling server for adaptive web systems. Proceedings - CNSR 2007: Fifth Annual Conference on Communication Networks and Services Research, 117–124. http://doi.org/10.1109/CNSR.2007.35.

© COPYRIGHT UPM