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Editorial Preface

From the Desk of Managing Editor...

"The question of whether computers can think is like the question of whether submarines can swim." — Edsger W. Dijkstra, the quote explains the power of Artificial Intelligence in computers with the changing landscape. The renaissance stimulated by the field of Artificial Intelligence is generating multiple formats and channels of creativity and innovation.

This journal is a special track on Artificial Intelligence by The Science and Information Organization and aims to be a leading forum for engineers, researchers and practitioners throughout the world.

The journal reports results achieved; proposals for new ways of looking at AI problems and include demonstrations of effectiveness. Papers describing existing technologies or algorithms integrating multiple systems are welcomed. IJARAI also invites papers on real life applications, which should describe the current scenarios, proposed solution, emphasize its novelty, and present an in-depth evaluation of the AI techniques being exploited. IJARAI focusses on quality and relevance in its publications.

In addition, IJARAI recognizes the importance of international influences on Artificial Intelligence and seeks international input in all aspects of the journal, including content, authorship of papers, readership, paper reviewers, and Editorial Board membership.

The success of authors and the journal is interdependent. While the Journal is in its initial phase, it is not only the Editor whose work is crucial to producing the journal. The editorial board members, the peer reviewers, scholars around the world who assess submissions, students, and institutions who generously give their expertise in factors small and large— their constant encouragement has helped a lot in the progress of the journal and shall help in future to earn credibility amongst all the reader members.

I add a personal thanks to the whole team that has catalysed so much, and I wish everyone who has been connected with the Journal the very best for the future.

Thank you for Sharing Wisdom!

Editor-in-Chief

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A Multi_Agent Advisor System for Maximizing E-Learning of an E-Course

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Abstract—Web-based learning environments have become popular in e-teaching through WWW as distance learning. There is an urgent need to enhance e-learning to be suitable to the level of learner knowledge. The presented paper uses intelligent multi-agent technology to advise and help learners to maximize their learning of an offered e-course. It will build its advices on the performance and level of education of learners including past and current learning. Most of advices are to guide learner to make exercises as quizzes or passing tests in different level of difficulties.

Keywords—AI; Agent; Multi_Agents; distant learning; e-Learning; e-Teaching; Education; e-Course

I. INTRODUCTION

In the time being, Distance learning is the hot issue in computer science. Online learning through the web has become popular in the decade [1]. E-learning is nowadays recognized as one of the efficient methods to respond to the requirements of open and distance learning. In the e-learning system, several traditional learning styles should be combined with the learner-centered approach. It needs a good notation to represent the requirements of the e-learning system [2].

In the dynamic changes information environment without prior modeling, it can independently plan complex operation steps to solve practical problems, can independently discover and obtain the available resources the learners needed and then provide the corresponding services under the circumstance that the learners do not take part in [3].

An agent is something that perceives and acts in an environment. The agent function for an agent specifies the action taken by the agent in response to any percept sequence [4]. Intelligent agents are task-oriented software components that have the ability to act intelligently. They may contain more knowledge about the needs, preferences and pattern of the behaviors of a person or a process as in [5].

The agent has to collect users' personal interests and give fast response according to the pre-specified demands of users. The personal agent can discover users' personal interests voluntarily without bothering the users. It is very suitable for personalized e-learning by voluntarily recommending learning materials [6].

Intelligent agents should have the ability of adaptive reasoning. They must have the capability to access information from other sources or agents and perform actions leading to the completion of some task. Also, they must control over their internal state and behavior and work together to perform useful and complex tasks. Thus, they should be able to examine the

external environment and the success of previous actions taken under similar conditions and adapt their actions [7].

Educators, using Web-based learning environments, are in desperate need for non-instructive and automatic ways to get objective feedback from learner in order to better follow the learning process and appraise the online course structure effectiveness. On the learner side, it would be very useful if the system could automatically guide the learner's activities and intelligently recommend online activities and resources that would favour and improve the learning. The automatic recommendation could be based on the instructor's intended sequence of navigation in the course material, or, more interestingly, based on navigation patterns, of other successful learners [8].

Currently, the state of intelligent is focused on one-to-one learning instruction. Some examples include ACT systems [8], DEBUGGY [9], and PIXIE [10]. Specifically, the kind of learning modality used is centered on learning by being told [11].

There are too much work done in the field of e-learning and e-teaching based on agent. Gascuena and Fernandez-Caballero [12] introduced an Agent-based Intelligent Tutoring System for enhancing E-Learning/E-Teaching, where agents monitor the progress of the students and propose new tasks. De Antonio presented architecture of intelligent virtual environment based on agent technology [13]. Also, a similar one for nurse training is offered in [14]. Tang offered the implementation of a multi-agent intelligent tutoring system for learning the programming languages [15]. According to Java Agent for distance education (JADE) frame work, Silveira and Vicari carried out their system Electrotutor which is Electrodynamics distance teaching environment [16].

Since the students and teachers are on different time and spare in an e-learning environment, the learning status of a student is difficult to be controlled by teachers. In current learning platforms, they neither analyze the causes of learning inefficiency of users, nor generate new learning material and testing. The former keeps the learners from not using these learning systems anymore because they are confusing; the latter leads to out-of-date materials and the learners could not get any new knowledge [17].

In the proposed work, there is multi-agent system that could get learner profile knowledge at his logging to the e-course. Then system can help users and advises them in their on line learning. It will enhance e-learning of e-courses through advising learners for better navigation through e-course contents by offering some links or jumping over course

resources, or by guiding learner to make exercises in a quiz or passing through an exam.

II. E-COURSE DELIVERY

One of the main goals of e-teaching is that the learner learns more and better to enhance teaching as well as learning. E-teaching should be able to facilitate the learning facilities, and to take into account in learning to introduce concepts to each learner.

The presented system incorporates multi agents, collaborated together to help in maximizing the learning process of an e-course. The course tested in this system is the Programming Language Concepts, as taught in Computer Science Department in Umm Al-Qura University, in Saudi Arabia. The task of the system is to enhance e-course navigation, which, by the way, improves e-learning process.

The main goal of the proposed system is to maximize the course learning. It will acquire knowledge directly and indirectly about learners. Direct knowledge includes preferences and level of education of learners (current knowledge). While indirect knowledge includes learner's ability and efficiency of learning (new knowledge), which is gathered from results of any assessment (exercise, quiz or test). All of these knowledge are stored in the learning KDB.

Before using the system to navigate course materials (domain), the learner should open an account, and get a password, to be able to log in. The learner should feed the system with some personal knowledge, to be stored in the Learning KDB. This knowledge includes historical education level.

At logging in the system to navigate the material of the e-course, the learner will see the menu which include main topics of the course, which represent the main part which is the theory pages. Each of these pages could posses with any media: text, graphic, image, audio, video, or even links to an external page.

Also, the e-course material includes two important parts: quizzes and tests which are all considered assessment for each topic or the whole course topics. Quizzes are created from exercises, in a way to complete the understanding of the theory material pages. Delivering of any part of the e-course (material, quiz, or test) and relative advices is done inconsequence manner as will be described in section IV.

III. STRUCTURE OF MULTI-AGENT E-LEARNING SYSYTEM

The proposed e-learning advisor system is structured basically, as shown in Fig. 1, from three modules; each of them represents a knowledge level. The domain module includes the material and assessments (exercises and questions) of topics of the e-course to be taught to the learner. While the learning module represents the knowledge that already known by the learner (personal knowledge, historical learning level and the newly acquired knowledge from the coming e-courses) . Finally, pedagogical module holds rules and strategies of teaching the course materials (fundamentals of teaching).

Strategies of pedagogy specify how the sequence of materials, what kind of feedback has to be given during education, when and how the course contents (problems,

definition, example, and so on) have to be shown or explained [18].

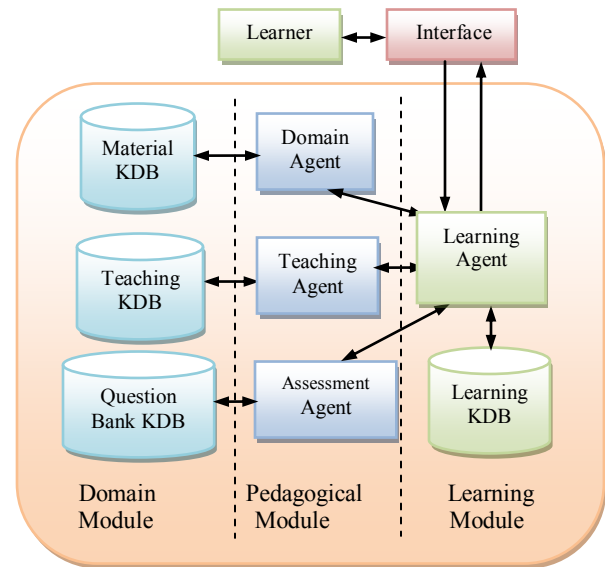


Fig. 1. Structure of the multi-agent advisor system.

The presented system includes the following knowledge Databases (KDB) and agents:

- Material KDB holds the e-course material or pages. Each page could include text, graphics, audio, video, or links to external pages
- Question Bank KDB holds question and exercises in two level of difficulties for each topic of the e-course.
- Teaching KDB holds the prerequisite and the sequence of presenting each topic. It also holds guidance and advices.
- Learning KDB holds account and personal information of and learning performance level of learners. It includes historical and new learning knowledge of learners.
- *Learning Agent* [Lagent] is the main agent in the system. It is responsible of many tasks including managing the learning process, controlling all other agent in the system.. Also, it interacts with the learner to acquires his account personal information and stores it in the learning KDB and consult all materials, assessments and advices to him. It receives assessment results from Aagent and evaluate learning efficiency of learner and update the learning KDB.
- Domain Agent [Dagent] receives a request to consult pages of certain topic from Lagent.
- Assessment Agent [Aagent] which is an external agent system for creating an assessment (quiz or test) automatically [19]. It receives a request from Lagent to build an assessment to be conducted to the learner, under some conditions. This agent selects exercise or questions randomly to creates quizzes or tests with two level of difficulties for each topic(s) from the course

material. It also grades the assessment and gives correct answers for each question.

- Teaching Agent [Tagent] retrieves the prerequisite of each topic or page in the course material page. It also retrieves learning level and performance of each learner from learning KDB through Lagent. Then, it passes its advice and guidance as a message to learner.

IV. THE LEARNING PROCESS

The learning process is done in the presented system as shown in Fig. 2. Sometimes, the system offer its advice for all learners, while navigating certain page, as help, or suggesting alternative pages, or guidance page

The main target of the proposed system is to advise the learners of an e-course to read certain pages or to navigate through some suggested links. Those pages or links, which represent actions to be done by learners, will help them to improve their knowledge and understanding of e-course materials.

Suggestion of those actions is triggered by events (learning activities) done by learners such as starting or finishing certain part of e-course material, jumping to advanced part of e-course material, attempting to perform a simulation, passing through an assessment (quiz or test), and accessing certain part of e-course material or even external link.

According to learner's level and performance in the Learning KDB, Lagent will decide if the learner needs an advice. This decision is done by accessing the learning KDB, to enable Lagent to evaluate the performance of the learner. This KDB includes his level of education (already known knowledge), prerequisites (knowledge should be known before learning) for each page-material accessed by learners, assessments (quizzes, exercises, tests) should be passed by the learner in what minimum correctness percentage and maximum time.

In this case, Lagent will constitute its advice to the learner accordingly. If the learner has to be advised, the agent will look up in the e-course for the materials or media that should be taught to that learner to maximize his learning for that e-course.

This advice will guide the learner to access a link(s) which will include a media. This media could be one of the following classes: theory page(s), an assessment(s), and/or event voice or video files. All of these classes may be included in the same course, other courses, or Web sites.

Finally, the agent offers its advice to the learner. If the learner followed the advisor agent, his learning and performances will be improved.

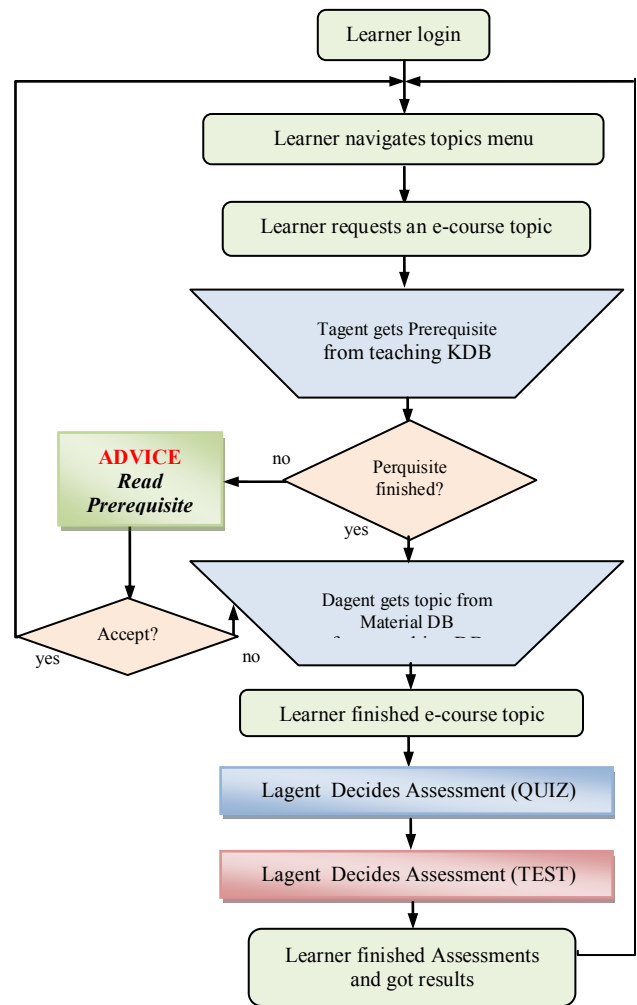


Fig. 2. The Learning Process.

V. ADVISING THROUGH ASSESSMENTS

The system will improve the learning process by an intelligent agent for advice and assistance. It causes learners to be as have an e-course suitable to their level of education, learning ability and assessment results. The intelligent agent will guide learners to their needed course materials to decrease any learning confusion. Fig. 3 and Fig. 4 demonstrate the advising process

A. Advising Actions

Testing scores of learners is always used to estimate their efficiency, and is divided into different levels in the traditional learning. During the learning activity, the behaviors of learners can be recorded in a database. This information can find out learners adaption to the teaching material and modify the level of learners.

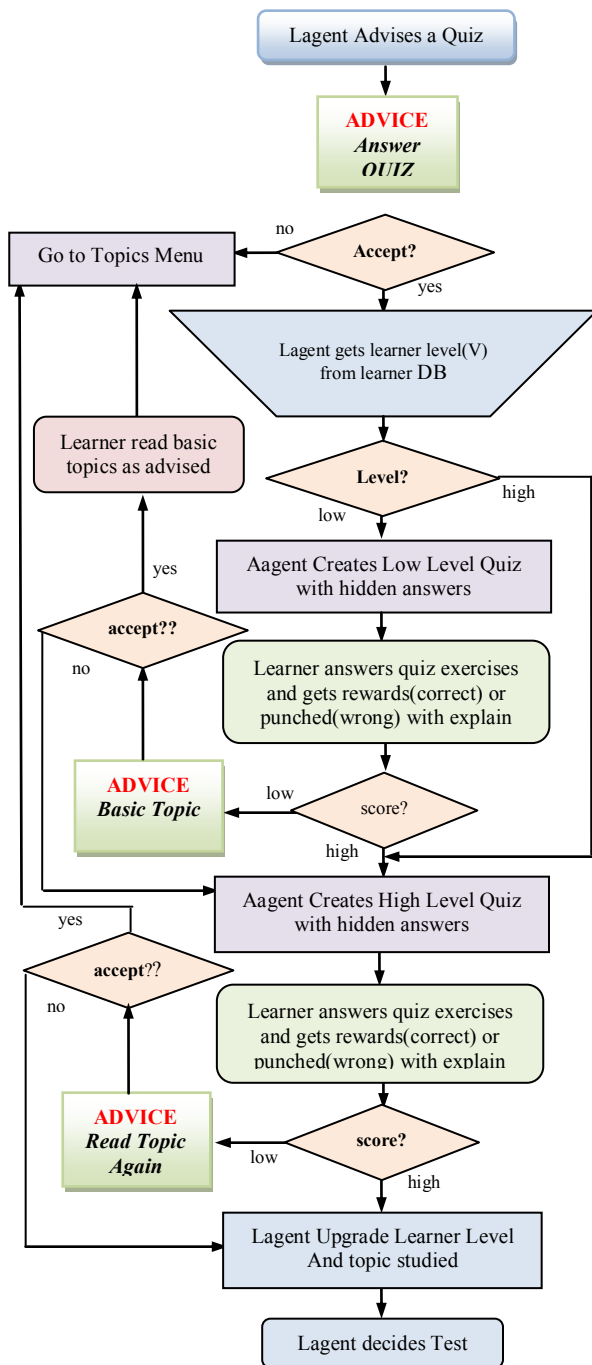


Fig. 3. The Quiz Process.

Sometimes, certain learner gets bad results after passing through an assessment (exam or quiz). This event will trigger an advising action. That event will activate Tagent, which will try to locate one sequence of action from previous sequences of actions taken with the event.

Then the agent will advise the current learner to visit and read some pages, which include important course material.

As example of advice, if the event is passing through an assessment, the advice is navigating a sequence of pages or media. It is not applicable to advise a learner by certain page or media that could directly be reached form the current page or media or by shortcut. So, the system takes care at offering its advice, not to include that case.

Tagent checks test results of assessments (as passed from Aagent) for each learner. According to these results, the agent will find the appropriate learning sequence for each learner and advises him through the learning process. The agent will advise the learner to get efficient learning time with useful e-course material.

B. Passing Through a Quiz

After navigating all pages of certain topic, Lagent will decide to enforce learner to pass through assessments like quizzes and test. Each quiz consists of 2-4 exercises. There is two level of exercise. The quiz level is specified, as shown in Fig. 3, according to the performance level of the learner.

Lagent gets the level of performance of the current learner from the learning KDB and decides the level of quiz. It asks Aagent to create the suitable quiz accordingly. Exercises will not be not too difficult. In the low level quiz, exercises will be small and in similar words as taught in topic. It will be accompanied with helpful figure or images. While in the high level quiz, question will be more difficulty.

While the learner is making exercises of a quiz, he will input his answer for each exercise to the system. The system reaction will be accompanied by reward or punishing for a correct or wrong answer for any assessment. This is always done through blinking text or image to show certain media such as a text, table, video, audio, picture or even graph. This is done as in the most of the learning systems. Then, Lagent gives its advice to the learner according to his results, as shown in Fig. 3.

C. Passing Through a Test

When the learner finishes the high level quiz, Lagent will update the learning KDB according to quiz results. Then Lagent will advise learner to pass through a Test, as shown in Fig. 4. It will ask Aagent to create a test consists of multiple type of questions.

Tagent is able to create exams from bank of questions randomly for certain topic(s). There are four types of questions: True/False questions, Multiple Choice questions, Fill in the Blanks questions, and Non-standard questions. After finishing the exam, Tagent will evaluate answers and pass scores to Lagent. Then Lagent will update learner level and performance in the learning KDB. Also, it stores that the topic is navigated and tested by that learner.

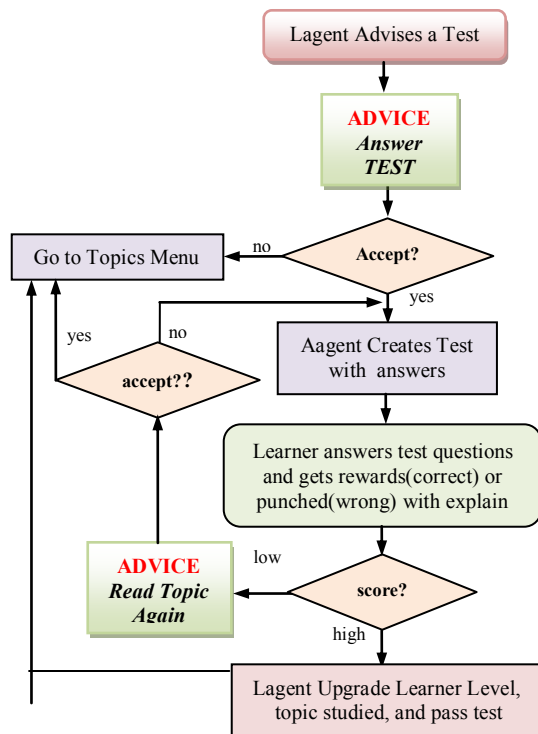


Fig. 4. The Test Process.

VI. CONCLUSION

The presented paper provided a multi-agent based advisor system to guide and advise learners of e-courses. It is suggested to advise learners in the Concepts of Programming Languages course. It is based on multi-agent technology. Agent built its advice on the past and current knowledge learnt by learners. It calls another agent was built to create quizzes and exams automatically in different level of difficulties and grades answers. Future work will extend applying that system in Computer Sciences courses. Also, it will be upgrading it to offer more adapted e-course.

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Implementation of an Intelligent Course Advisory Expert System

Cased-Based Course Advisory Expert System

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Abstract—Academic advising of students is an expert task that requires a lot of time, and intellectual investments from the human agent saddled with such a responsibility. In addition, good quality academic advising is subject to availability of experienced and committed personnel to undertake the task. However, there are instances when there is paucity of capable human adviser, or where qualified persons are not readily available because of other pressing commitments, which will make system-based decision support desirable and useful. In this work, we present the design and implementation of an intelligent Course Advisory Expert System (CAES) that uses a combination of rule based reasoning (RBR) and case based reasoning (CBR) to recommend courses that a student should register in a specific semester, by making recommendation based on the student's academic history. The evaluation of CAES yielded satisfactory performance in terms of credibility of its recommendations and usability.

Keywords—Academic advising; expert system; case-based reasoning; JESS; rule-based reasoning; evaluation

I. INTRODUCTION

The quality of academic advising received by a student is crucial to the overall performance of the student. Good advising yields a good outcome while bad advising will be frustrating and have a damaging effect on students' progress. However, a staff advisor needs to keep up with the academic history of advisees in order to be an effective guide. Academic advising requires a lot of patience, commitment and ingenuity, which does not always exist, because humans have their limitations. In many scenarios, the rules for guiding students may change from time to time due to curriculum reviews, changes in course structure, or the circumstances of specific students. This makes it necessary for the human advisor to be adept in all the nuances of academic advising at all times. In many academic departments, the roles assigned to staff may change periodically, making it compulsory for the staff concerned to learn new rules that pertain to advising a new set of students. In addition, academic advising is time-consuming and mentally exacting, requiring the application of psychological and people management skills. All of these present a complex scenario that requires good decision-making, which places huge responsibility on the human advisor. Therefore, there is a need to alleviate the drudgery associated with academic advising by using expert systems to aid decision-making.

The use of an expert system will ensure the automation a significant part of the advisory process in a way that allow

humans to do what they can do best, while the system complements human expertise by doing what it can do best, thereby creating a synergy that benefits both staff and students. Hence, the essence of a course advisory expert system is not to replace the human advisor, but to minimize the cognitive load and the time expended by the human advisor on academic advising, and to improve the quality of academic advising.

Course advising involves an academic staff giving counsel to a student on the courses to register in a semester in order to satisfy established academic requirements that pertain to the student's academic programme. Students in a University are generally expected to satisfy some performance criteria in order to progress from one level to another, with a specified number of credit units to be passed among a set of compulsory (core), electives, and optional courses. The role of the human course adviser is to ensure that a student makes good decisions on courses that should be registered relative to the student's current level and academic history in order to satisfy the graduation requirements. The course advisory task is a domain for the application of expert system because – it is based on the use of domain specific knowledge, uses voluminous data, it is difficult to characterize accurately, the curricular do change from time to time, and decisions have to be made based on the specific rules of the University concerned. A lot of the decisions made by a human advisor during the process of advising a student are based on reasoning drawn from previous episodes and experiences that the advisor had gained over time, and known rules of the University that relates to course registration. This suggests that a model of expert system that uses Case Based Reasoning (CBR) and rule-based reasoning for decision-making would be viable for academic advising.

CBR is a pattern-based problem solving paradigm that relies on knowledge gained from previous episodes to resolve new problems whenever sufficient similarity can be established between the current case (problem) and past cases that are stored in the case base (repository) [1]. The attraction for using CBR as the mode of reasoning for academic advising is because many similarities exist in the nature of academic problems and concerns that students' have in the process of course registration. Hence, the combination of CBR and rule-based reasoning – which enables the consideration of specific university rules for decision making – in order to develop an expert system for student advising. A case based approach will seek to emulate human expertise to a reasonable extent, by

drawing on the similarity that exist in the experiences gained in previous cases of course advising, and an awareness of relevant university rules.

This paper describes the implementation of an intelligent course advisory expert system (CAES). The expert system uses the combination of rule-based reasoning and case-based reasoning to generate credible recommendation to guide students on courses to register. The objective of the system is to reduce the effort, and time used in the process of student advising, and to improve quality.

The remaining part of the paper is described as follows. In section 2, we present related work. Section 3 discusses the course registration process and the requirements for a Course Advisory Expert System (CAES). Section 4 gives a description of the architecture of the CAES and the process of applying the CAES. Section 5 gives an outline of algorithms that enable some of the core functionalities of the CAES. Section 6 reports a case study of the application of the CAES in a tertiary institution. Section 7 is a preliminary evaluation of the CAES, while the result and discussion was presented in Section 8. The paper is concluded in section 9 with a brief comments and outlook of work for the future.

II. RELATED WORK

The desire for technology-supported academic advising has been around for a while, and a number of efforts have been reported in the literature. In [2], the evaluation of a Web-based decision support tool that aids student advising was reported. The evaluation of the tool showed that large percentage of respondents regard it as effective and efficient for academic advising, however, the details of its implementation was not provided in the paper. In [3], the design of an i-Counselling system that combines ontology-based information retrieval and optimization-based search technology to provide relevant answers to queries posed by new and current students was reported. The academic advising module of the system is able to answer questions from current students on specific programmes, study plans and graduation requirements. The system was adjudged effective after an evaluation was conducted. The HE-Advisor [4], is a multidisciplinary Web-based higher education advisory system that offers academic advisory services in order to help students make the best decision in selecting a degree to study. It also incorporates guidance on course registration to assist students to stay on the right path towards concluding their degree, information on graduation requirements and statistics for timetable planners were also provided by the system. The ViCurriAs [5] is a visual tool that facilitates the registering of new curriculum plans and track the progress of students enrolled for a degree programme.

Other types of expert systems or hybrid intelligent systems that have been used for academic advising include [6, 7, 8]. In addition, in [9], the concepts of intelligent agents and semantic web were used to develop an academic advisory system. The domain knowledge was modeled by using the OWL ontology language, while the agents reason on stored domain knowledge by using an inference engine. The work in [10] presents the architectural framework of an intelligent advisory system that uses the concepts of object-orientation and

knowledgebase rules for academic advising. The objective of the system is to help students to know what to do and how to do it.

In [11] the Interactive Virtual Expert System for Advising (InVESTA) was reported. InVESTA was designed to assist undergraduate students and their advisors in providing timely, accurate and conflict-free schedules. The system was implemented using Java and an object-relational database. It comprises a Database Layer, Transaction Layer, Scheduler and the web-based Front-End.

The Graduate Course Advisor (GCA) is a rule-based expert system that advises graduate students of computer science [12]. The GCA is a Prolog-based system that was modelled after MYCIN. GCA divides advising into four phases such that each phase may apply the inference engine to its own rule base and invoke other procedures. The CBR Recommender for Academic Advising (AACORN) was presented in [13]. AACORN uses course histories to generate recommendations for course advising. By reusing the knowledge embedded in a student's academic history as captured in student's transcripts, AACORN is able to make reasonable suggestions with a limited amount of domain knowledge. The edit distance was used to determine the similarity between the course history of a new student and other course histories in the case base.

The intelligent Course Advisory Expert System (CAES) presented in this work differs from other course advisory system because it integrates the use of CBR and rule-based reasoning to generate intelligent recommendations for students on courses to register. The merit of the CAES when compared to many of the previous approaches is the relatively cheap cost of knowledge acquisition and representation.

A CBR system like the CAES is able to acquire new knowledge as usage of the system increases, while its rules can also be modified with minimal effort. This is unlike when an ontology is used for knowledge representation, which although, quite effective, require an advance investment in quality ontology development before efficient course advising can be obtained. Hence, as a contribution, this work offers a cheaper but cost effective way for implementing expert-based academic course advising. In sequel section, we shall discuss the architecture of system in more detail.

III. AN OVERVIEW OF THE COURSE REGISTRATION PROCESS

The procedure for course registration by a student entails a series of activities. The procedure includes:

- 1) *authenticate the status of student to determine if student qualify to be registered into a particular level based on previous academic performance;*
- 2) *select a course to be added to the list of registered courses by student;*
- 3) *add or drop a course after initial registration; validate course prerequisites; and*
- 4) *check the rules that guides total numbers of course to register and the combination of courses to register.*

It is expected that for a healthy process both the student and the advisor must have adequate understanding of the procedure in order to avoid violations. Fig. 1 shows the key uses cases that pertain to a course registration scenario. A more detailed analysis of the use cases captured in Fig. 1, revealed a number of specific requirements that a course advisory system must meet. These include:

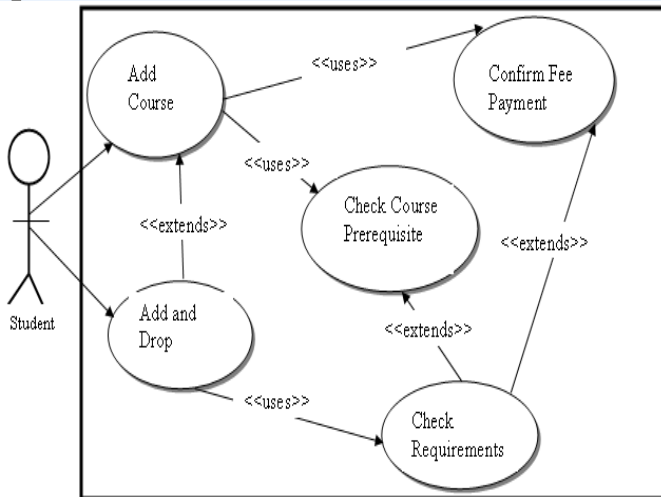


Fig. 1. A Use Case Diagram of the Course Registration Process

- 1) The System shall be able to authenticate the status of every user as either a valid student user or staff user.
- 2) The System shall only allow courses to be added or dropped during the date period allocated for course registration.
- 3) The System shall capture detailed general student information including the department, level, and college.
- 4) The System shall capture detailed information on students examination results including the failed, passed and dropped courses.
- 5) The System shall capture all relevant university rules that pertain to registration.
- 6) The System shall be able to give recommendation to a user once the valid status of the user is determined.
- 7) The System shall provide explanation for all recommendations suggested to the user.
- 8) The System shall provide real-time feedback when the user requests a recommendation.

These set of requirements provided the basis for the design and implementation of the CAES.

IV. ARCHITECTURE OF THE COURSE ADVISORY EXPERT SYSTEM (CAES)

The CAES is based on a three-tier architecture that consists of a presentation layer, a middle layer and a data layer (see Figure 2). The presentation layer enables the user to access the application via a browser by using client devices such as desktop, laptop, or mobile phones. The various graphic user interfaces (GUIs) through which the user interacts with the system are contained in this layer.

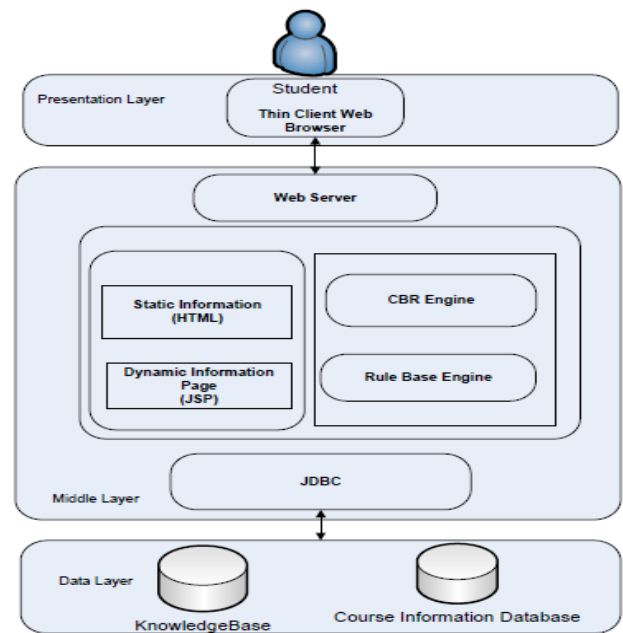


Fig. 2. The 3-tier architecture of the system

The middle layer consists of the Web application server, which facilitates communication in form of requests and notifications between the clients and the CAES application using the HTTP protocol. Apache Tomcat was used as the web application server for the CAES. The middle layer also contains the rule-based engine (RBR), which was implemented using Java Expert System Shell (JESS)¹ in order to enable reasoning on the rules that pertain to student registration; the case-based reasoning (CBR) engine enables case based reasoning. The RBR and CBR engine are deployed on the web application server. The middle layer also contains the Java servlets and JSP components that provided basis to weave java codes round the RBR and CBR engines of the CAES. The Java Data Base Connectivity (JDBC) protocol that enables interaction with the data layer of the architecture is also a contained in the middle layer.

The Data Layer contains the data and knowledge artifacts that the system relies on to deliver its functionality. This layer consist of a knowledge base that contains the facts and rules (Jess fact files and rules) that is used by the RBR engine, and the relational database that contains information on all courses that are available in the University.

A. Using the CAES for Advising

In order to use the CAES for academic advising, the user will need to do the following:

- 1) Input a valid identification number at the CAES GUI
- 2) If successful, the CAES interface will display student details from the course information database. Displayed

¹ <http://herzberg.ca.sandia.gov/>

information will include current cumulative grade point average (CGPA), passed courses with grades obtained, failed courses, dropped courses, and the set of courses to register for the current semester.

3) Click recommend to generate a list of suggested courses to register for the new semester

4) Click on view explanation to see rationale for recommended courses.

The Inference engine comprising of the rule engine and the CBR engine are used to generate recommendation of courses to be registered in a current semester.

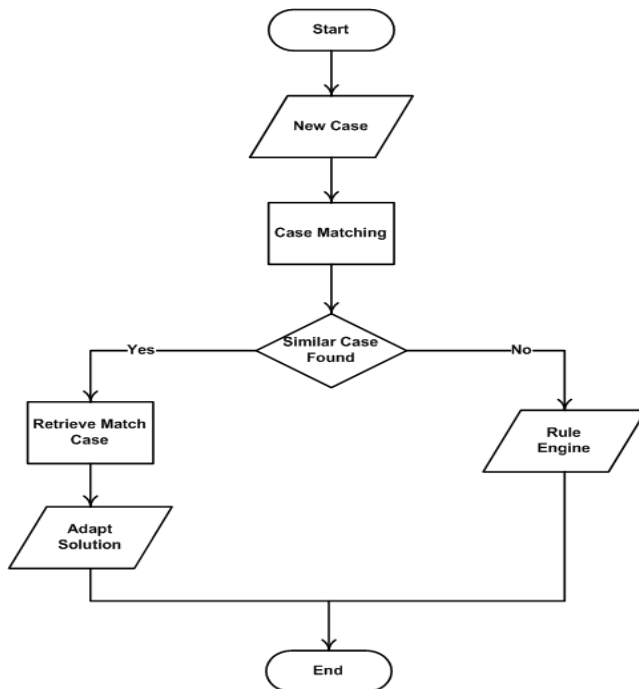


Fig. 3. Schematic representation of CAES recommendation

The Inference mechanism checks to see if there are previous cases that are similar to the current case by taking note of the courses failed and dropped by a student and his current level. All of these factors are considered in generating an advice for the student. Case based reasoning is used because the system computes a recommendation by scanning the case base for instances that are similar to the one at hand and adapts the most similar old solution in a new scenario. The report is sent back to the student via the CAES GUI. If no similar case exists then rules contained in the knowledge base are used to construct a recommendation based on deductions that can be made using information available on student's level, failed courses, failed prerequisites, and maximum total of credits that can be registered. CAES retains in the case base, all cases that have been handled successfully.

An investment to be made in order to productively engage the CAES is that an administrator must continually maintain the case base to ensure that course information and the rules in the knowledge base are regularly updated. This is to ensure that the CAES system have the correct basis to make its recommendation during academic advising.

The Figure 3 is a schematic representation of the recommendation process of the CAES using a program flowchart.

V. THE REASONING MECHANISM OF THE CAES

In this section, we give some insight into the reasoning behind some of the recommendations of the CAES.

When CAES starts, the student course information is considered as a new case. CAES then computes a similarity score for the new case using the algorithm.

$$\text{Similarity } (NC, OC) = \frac{\text{common}}{\text{common} + \text{different}}$$

Where *NC* is the new case, *OC* is the old case present in the case base.

Common refers the matching pair between the new case and an old case.

Different refers the mismatch pair between the new case and an old case.

The case with the highest similarity score is picked as the candidate for adaptation in order to recommend to a user the courses to register. If a similar case does not exist, then a decision algorithm based on the rule engine is used to generate recommendation. The case adaptation procedure is rule-based, whereby university rules are used to guide selections.

Three rules were used 1) a course with a higher credit unit should be selected over a course with a lower credit unit; 2) compulsory courses take precedence over electives and optional courses; and 3) a course that is pre-requisite for another that is failed, should be considered over courses that are not prerequisite for any other course.

VI. CASE STUDY AND DISCUSSION

A case study of Covenant University a tertiary institution based in Ota, Nigeria was undertaken using students of the Computer Science study program of the University as subjects. For a student intending to register a course at the beginning of a new semester these scenarios exist.

- 1) The student could have just the current semester course to register.
- 2) The student could have failed course(s) alongside the current semester courses.
- 3) The student could have dropped course(s) alongside the current semester courses.
- 4) The student could have failed and dropped course(s) alongside the current semester courses.

In recommending the set of courses to register for the current semester, CAES uses the scenario above that is applicable to that particular student together with the set of rules outlined in the University policy for course registration, putting into consideration the different course status (course prerequisites, compulsory or elective courses). The different conditions were modelled as rules and stored in the knowledge base of CAES. The following are the set of algorithms

showing the rationale for specific scenarios that are captured in the knowledge base of CAES.

The REGISTERDROPPEDFAILEDOURSE algorithm in Table 1 caters for the scenarios i) - iii), while the REGISTERCOURSE algorithm in Table 2 caters for scenario

iv). Table 3 shows sample JESS rule that states that a compulsory course have precedence over other types of courses. Also, Figure 4.1 and Figure 4.2 show snapshot of the CAES application.

TABLE I. REGISTER DROPPED AND FAILED COURSES ALGORITHM

Algorithm REGISTERDROPPEDFAILEDOURSE (V, E, S)
Input: A vector V of courses failed and/or dropped in the previous session of the same semester, E a vector of elective courses and S a vector of courses to register in the current session of the same semester.
Output: A vector R containing the list of courses recommended for registration by the student in that semester.

Initialize R.
 [Considering Failed and Dropped courses]
 for all courses $v_i \in V$ ordered by coursecode in ascending order
 while registeredCredit < maxRegistrable AND $i < \text{count}(V)$
 Add v_i to R.
 registeredCredit \leftarrow registeredCredit + courseCredit(v_i)
 increment i.
 [Considering failed prerequisite course]
 If registeredCredit < maxRegistrable
 for each course $C_j \in S$
 while registeredCredit < maxRegistrable AND $j < \text{count}(S)$
 if prerequisite(C_j) is failed OR dropped
 then Add C_j to D
 else
 Add C_j to R
 $S \leftarrow S - C_j$
 registeredCredit \leftarrow registeredCredit + courseCredit(C_j)
 increment j.
 [For the remaining courses]
 If registeredCredit < maxRegistrable
 for each course $K_p \in S$ that is compulsory ordered by course credit in descending order
 while registeredCredit < maxRegistrable AND $p < \text{count}(S)$
 Add K_p to R
 registeredCredit \leftarrow registeredCredit + courseCredit(K_p)
 increment p.
 If registeredCredit < maxRegistrable
 for each course $M_e \in E$ that is elective
 while registeredCredit < maxRegistrable AND $e < \text{count}(E)$
 Add M_e to R
 registeredCredit \leftarrow registeredCredit + courseCredit(M_e)
 increment e.
 return the vector R containing the list of recommended course for the semester.

TABLE II. REGISTER COURSES ALGORITHM

Algorithm REGISTERCOURSE (E, S)
Input: A vector E of Elective courses and S a vector of courses to register in the current session of the same semester.
Output: A vector R containing the list of courses recommended for registration by the student in that semester.
 R \leftarrow NULL [initialize R]
 for each course $C_i \in S$
 while registeredCredit < maxRegistrable AND $i < \text{count}(S)$
 if prerequisite(C_i) is passed
 Add C_i to R
 registeredCredit \leftarrow registeredCredit + courseCredit(C_i)
 increment i
 If registeredCredit < maxRegistrable
 for each course $K_j \in S$ that is compulsory ordered by course credit in descending order
 while registeredCredit < maxRegistrable AND $i < \text{count}(S)$
 Add K_j to R
 registeredCredit \leftarrow registeredCredit + courseCredit(K_j)
 increment j
 If registeredCredit < maxRegistrable
 for each course $M_e \in E$ that is elective
 while registeredCredit < maxRegistrable AND $e < \text{count}(E)$
 Add M_e to R
 registeredCredit \leftarrow registeredCredit + courseCredit(M_e)
 increment e
 return the vector R containing the list of recommended course for the semester.

TABLE III. SAMPLE JESS RULE TO SELECT A COMPULSORY COURSES

(defrule recommend-compulsory-course
 "If there is a compulsory course, recommend for registration"
 ;; The course belongs to the type department and is compulsory
 (course (belongsTo department) (ccode ?code)(ctitle ?title)
 (cunit ?unit) (cstatus compulsory))
 ;; and we haven't recommended this type yet
 (not (recommendcourse (ccode ?code) (ctitle ?title)))
 =>
 ;; Recommend the course.
 (assert (recommendcourse (ccode ?code) (ctitle ?title) (cunit ?unit) (because "compulsory departmental course"))))

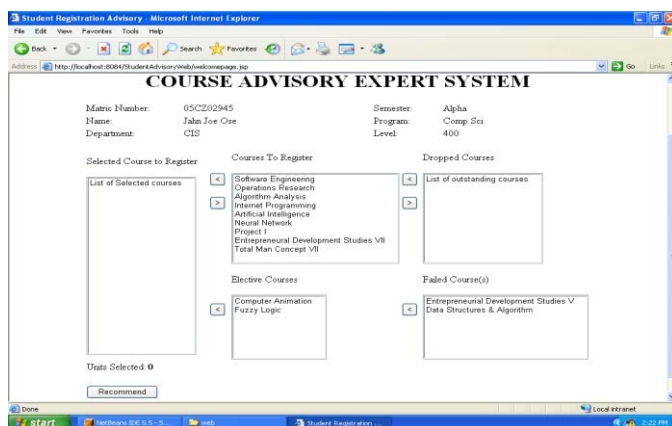


Fig. 4. The CAES Interface

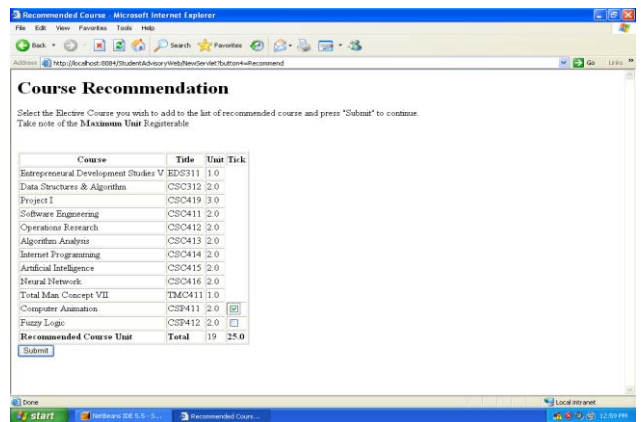


Fig. 5. CAES Recommendation Page

VII. EVALUATION

Human experts conducted a usability evaluation of the prototype in order to assess the level of user satisfaction with the system. This was then validated through the direct method of evaluating expert systems as used by Salim et al. [14].

A small experiment to test the system’s recommendations against those of human advisors was conducted using the direct method. Course Advisers across each level from the Department of Computer and Information Sciences of Covenant University were asked to participate in the survey. Each received an identical set of questionnaire, and had a running version of CAES installed for them. The course advisers were asked to rank the recommendation of CAES on a likert scale of 0-5 to assess the degree of how true or false are the recommendations of CAES. A brief overview of the direct method of expert system evaluation used by each evaluator is as follows:

- 1) The evaluator is given a sample copy of the software system - CAES to be evaluated.
- 2) The evaluator selects a benchmark problem, based on his experience, and runs this problem on CAES.
- 3) After running the bench-mark problem, the evaluator responds to a set of questions (14) in the questionnaire instrument and estimates a quantitative answer to each question on a 0 to 5 scale with 5 being very true and 0 being very false.
- 4) Each numerical result is multiplied by a weighting factor as given in the weight column.
- 5) The weighted values are summed and then divided by the sum of the weights (19) to give a result in the numerical range of 0 to 5.

The Figure 6 gives a computation of the evaluation experiment conducted by one of the evaluator.

A subset of the summary result in calculating the experimental evaluation of the evaluators is given in the Table 4.

TABLE IV. RESULT OF EVALUATION EXPERIMENT

Evaluator	Computed Satisfaction Level
1	4.00
2	4.16
3	4.21
4	3.52
5	3.57
Mean Satisfaction Level	3.89

	Question	Asses sment Value	Weig ht	Value X Weight
	Correctness of Answer			
1	Is there enough information to evaluate the software?	4	(2)	8
2	Does the software give the same answer that a human advisor would give?	5	(2)	10
3	Does the software provide the right answer for the right reasons?	5	(2)	10
	Accuracy of Answer			
4	Is the software accurate in its answer(s)?	5	(2)	10
5	Is the answer complete? Does the user need to do additional work to get a usable result?	4	(2)	8
	Correctness of reasoning technique			
6	Does the answer change if new but irrelevant data is entered into the software?	5	(1)	5
7	Does the system require a lot of irrelevant question to reach its answer?	0	(1)	0
	Sensitivity			
8	Does the answer change if irrelevant changes are made to the system rules?	5	(1)	5
	Reliability			
9	Does the software crashes or hang ups in its host computer?	2	(1)	2
10	Does the system give warnings for cases involving incomplete data or rules?	5	(1)	5
	Cost Effectiveness			
11	Does the software still provide answers with incomplete knowledge	2	(1)	2
12	Is the cost of the system justified by its performance?	5	(1)	5
	Limitations			
13	Can limitations of the system be detected at this point in time?	4	(1)	4
14	Can the system learn from increased data or experience?	2	(1)	2
	Result = $\Sigma (\text{weight} \times \text{value}) / \Sigma (\text{weight})$		19	76
				4.00

Fig. 6. Evaluator’s questionnaire

VIII. RESULT AND DISCUSSION

From the statistical analysis of the results obtained from the evaluation of the human experts that participated in the experiment, CAES had a mean satisfaction level score of 3.89 out a maximum of 5.0, which is indicative of a 77.8% level of user satisfaction.

The implication of this result is that after the experts have considered important metric dimensions such as correctness of answer, accuracy, quality of reasoning technique, sensitivity, reliability, cost effectiveness, and observed limitations of the system, the system obtained a mean rating of 77.8%. This connotes an appreciably good rating for the CAES system, and an indication of its viability to support the task of academic advising.

IX. CONCLUSION

The CAES system that was developed is intended for use in a mid-range university. Its experimental version was successfully trialed by the Department of Computer and Information Sciences of Covenant University. The modular structure and web-based design of the CAES makes it suitable to be launched and used in other departments of the University.

In our future work, we shall improve on the case revision and case adaptation capability of the CAES, because we observed some complex cases, which the system did not handle adequately. This had to do with students that have changed from one programme to another - many of them more than once - , and have failed and dropped courses that are spread among different departments. We observed that in such scenarios, it was difficult for the current implementation of CAES find good cases to use as basis for adaptation to construct a recommendation. We do not consider this a major drawback of CAES, because even for the human course adviser, cases where a student has failed multiply in different departments are more intricate to handle, yet we seek to improve CAES in these areas.

As its contribution, this work offers a demonstration of application of artificial intelligence technology (AI) to support academic advising, which is very crucial to the academic well-being of students. The CAES was not intended to eliminate the role of human (staff) advisors, rather it enables students to concentrate on real issues that pertain to course registration, and affords unrestricted access to expert advice thereby reducing the burden placed on the human advisor.

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External analysis of strategic market management can be realized based upon different human mindset – A debate in the light of statistical perspective

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Abstract - The paper entails the statistical correlation of the investigations carried out for the sales and profit prediction and analysis by persons of different mindsets in case of strategic uncertainty. The paper by virtue of statistical and fuzzy logic based justifications has pointed out certain discovered facts in this perspective. The normal, optimistic, pessimistic and fickle-minded based individual mindsets significantly contribute to varying external analysis of business statistics.

Keywords - statistical correlation, fuzzy logic, optimistic, pessimistic, fickle-minded, business statistics

I. INTRODUCTION

Strategic development or review[1] deals with an analysis of the factors external to a business that affect strategy. In strategic market management, estimation of sales and profit plays a significant role. Sometimes a separate statistical analyst team is solely recruited in certain business companies. A running business can be investigated on the basis of apriori events and statistical trend analysis[2,3]. However in certain cases due to some external stochastic events, statistical analysis has to be carried out based upon prediction and forecasting and in this perspective of strategic uncertainty, the business estimate varies from individual to individual depending on his nature viz. normal, optimistic, pessimistic and fickle-minded.

II. VARIATION OF EXTERNAL ANALYSIS OF STRATEGIC MARKET MANAGEMENT BASED ON HUMAN MINDSET

Certain discovered facts can be pointed out pertaining to the variation of external analysis of strategic market management depending on the human nature. We propose certain mathematically established axioms in this context. An

opportunity or a threat results in a significant change in pattern of the sales and profit of a business. Marketing Myopia[4] also indicates the essence of investigation of sales and profit in case of strategic uncertainty. Furthermore, profit and loss are two mutually exclusive events at any specific timing instant of the observation period. Therefore, R , the Bernoulli random variable[5] for the external analysis of business strategy in this situation, can be viewed as –

$R = 1$ if profit occurs
 $R = 0$ if loss occurs.

R is a statistical indicator of X or Y .

Claim 1 - If prediction of occurrence of gain in a strategic market management by a normal individual is based upon estimation of weight of single associated parameter and hypothesis of fairness by pessimistic individual is rejected, then for unit negative bias, the estimate of weight of the single parameter by either historical or predictive means by a normal person is represented as a complex variable.

Illustration of Claim 1 –

In case of business uncertainty, predictive decisions among various business analysts differ considerably. A normal person will efficiently judge the current status of the business and try to predict in a concise manner.

In many cases it can be observed that optimistic, pessimistic and fickle minded persons predict the sales and profit status defying the current status and hence the statistical hypothesis as per their predictions are likely to be biased.

In this claim, we propose the correlation of estimation of normal person with a pessimistic individual.

The proposed mathematical equation of neuro-fuzzy based

event (gain) estimation between a pessimistic and a normal individual in case of strategic uncertainty is as follows-

$$T_p + \beta = AW_n = [(\sum_{i=1}^x AW_{x,i} * AW_{y,i}) / x] \dots\dots\dots(1)$$

where T_p = average accuracy estimation of gain by pessimistic individual,

β = unit negative bias value

AW_n = effective weight of the associated parameters per prediction by a normal individual

$AW_{x,i}$ = estimate of weight of i^{th} parameter on the basis of sampled historical information ,

$AW_{y,i}$ = estimate of weight of i^{th} parameter on the basis of present hypothesis,

x = total number of instances of the arrival of the event gain

As per our proposal , single incidence of gain takes place and hypothesis of fairness by pessimistic individual is rejected .

Therefore, $AW_{x,1} * AW_{y,1} = 0 + \beta$ or, $(AW_{y,1})^2 = \beta$

or, $(AW_{y,1})^2 = -1$ [since unit negative bias]

or, $AW_{y,1} = (-1)^{1/2} \dots\dots\dots(2)$

Similarly, we can show that $AW_{x,1} = (-1)^{1/2} \dots\dots\dots(3)$

Hence it is justified to state that “If prediction of occurrence of gain by a normal individual is based upon estimate of weight of single parameter and hypothesis of fairness by pessimistic individual is rejected , then for unit negative bias, the estimate of weight of the single parameter by either historical or predictive means by a normal person is represented as a complex variable”.

Claim 2 - Accuracy estimate of future prediction of occurrence of an uncertain event (gain or loss) is governed by the principle of hypothesis of fairness rule in case of both optimistic and pessimistic individuals.

Illustration of Claim 2 –

Strategic uncertainties focus on specific unknown parameters that will affect the outcome of strategic decisions. In this claim we have proposed that the principle of hypothesis rule plays a pivotal role in strategic decisions. A statistical hypothesis[6] is an assertion about the distribution of one or more random variables which we want to verify on the basis of a sample.

In this claim we represent mathematically the relation among predictive gain estimates done by normal , optimistic and pessimistic individuals.

$$P (| \beta_0 - \alpha_n | \geq \mu) = P (| \alpha_n - \beta_p | \geq \mu) = V \dots\dots\dots(4)$$

where β_0 = predicted value of percentage of gain by optimistic person in higher crisp form

α_n = predicted value percentage of gain by normal person being 0.5

β_p = predicted value percentage of gain by pessimistic person in higher crisp form

μ = estimate of deviation of both optimistic and pessimistic from actual outcome V ; $V \in \{ 0,1 \}$.

If $V = 1$, $P (| 1 - 0.5 | \geq (1-1))$ is valid and it reveals that prediction of optimistic individual is accurate and we reject hypothesis of fairness of pessimistic individual as $P (| 0.5 - 0 | \geq (1-0))$ is absurd.

Similarly, if $V = 0$, $P (| 1 - 0.5 | \geq (1-0))$ is absurd and it reveals that hypothesis of fairness of optimistic individual is rejected.

Hence it is justified to state that “Accuracy estimate of future prediction of occurrence of an uncertain event (gain or loss) is governed by the principle of hypothesis of fairness rule in case of both optimistic and pessimistic individuals”.

Claim 3 - In case of sales and profit estimation of strategic market management done by a fickle-minded person , the predicted value (T_v) clearly acts as a reference parameter for identifying the output (T_o) trends towards both rare and frequent fuzzy domains.

Illustration of Claim 3 –

Fuzzy set theory was proposed in 1965 by Lotfi A. Zadeh. A fuzzy set[7] can be defined mathematically by assigning to each possible individual in the universe of discourse, a value representing its grade of membership in the fuzzy set.

In definite form , crisp value is coined and it is in bivalent or binary variable state $\{0,1\}$, while the fuzzy value is in probabilistic form and lower and higher crisps indicate the lower and upper boundary limits of a fuzzy range. The average (0.5) is a threshold that indicates rare range ($0 \leq L_R \leq 0.5$) and frequent range ($0.5 \leq F_R \leq 1$).

The following table illustrates that in case of the sales and profit estimation of strategic market management done by a fickle-minded person, the predicted value (T_v) clearly acts as a reference parameter for identifying the output (T_o) trends towards both rare fuzzy (L_R) and frequent fuzzy domains (F_R). C_L and C_H represent lower and higher crisp values respectively.

Nature	If ($T_v < T_o$)	If ($T_v > T_o$)
Optimistic	$T_v = \{ F_R \}$	(i) $T_v = \{ F_R, C_H \}$

	$To = \{ C_H \}$	$To = \{ C_L, L_R, A_{VG} \}$ $(ii) Tv = \{ C_H \}$ $To = \{ C_L, L_R, A_{VG}, F_R \}$
Pessimistic	$(i) Tv = \{ C_L, F_R \}$ $To = \{ A_{VG}, F_R, C_H \}$ $(ii) Tv = \{ C_L \}$ $To = \{ L_R, A_{VG}, F_R, C_H \}$	$Tv = \{ L_R \}$ $To = \{ C_L \}$
Fickle-minded	$Tv = \{ A_{VG} \}$ $To = \{ F_R, C_H \}$	$Tv = \{ A_{VG} \}$ $To = \{ C_L, L_R, \}$

Table 1 : Gain estimation depending on different human mindset and

Hence it is justified to state that “In case of sales and profit estimation of strategic market management done by a fickle-minded person, the predicted value (Tv) clearly acts as a reference parameter for identifying the output (To) trends towards both rare and frequent fuzzy domains”.

Claim 4 - The null hypothesis of validity of an unknown event (gain or loss) for a biased individual is identical to alternate hypothesis of the same for a normal person.

Illustration of Claim 4 –

In this claim we have proposed that in case of strategic uncertainty, the general statistical rules of null and alternated hypothesis can be significantly correlated with the external analysis of strategic market management in the view of a biased (either optimistic or pessimistic) and normal person. Let p be unknown binary state of validity of an event (gain or loss) in case of biased individual and q_s is specific fuzzy estimate.

Therefore, $H_0 : p = q_s \dots\dots\dots(5)$

and $H_A : p \neq q_s \dots\dots\dots(6)$

where H_0 and H_A are null and alternate hypothesis respectively of biased person. In this context biased person indicates optimistic and pessimistic nature of a person.

Now, (1-p) is unknown binary state of validity of an event (gain or loss) in case of normal person and q_n be specific fuzzy estimate.

Since the event is valid, hence $q_s = q_n = 1$.

Hence, $H_0 : (1-p) = q_n \dots\dots\dots(7)$

and $H_A : (1-p) \neq q_n \dots\dots\dots(8)$

where H_0 and H_A are null and alternate hypothesis respectively of normal person.

Biased property reflects false belief which means Eq(5) is invalid. In that case the validity of Eq(6) concludes that $p \neq q_s$.Now q_s has to be in higher crisp whereby $p = 0$.

Let us examine whether Eq(7) is valid under this circumstance.

For Eq(7) to be valid, $(1-p) = q_n = 1$. Now q_n has to be 1 whereby $p = 0$. It indicates that alternate hypothesis of schizophrenic patient is identical to the null hypothesis of normal person, and vice-versa.

Hence it is justified to state that “The null hypothesis of validity of an unknown event (gain or loss) for a biased individual is identical to alternate hypothesis of the same for a normal person.”

III. CONCLUSION

The paper points out the following discovered facts –

1. If prediction of occurrence of gain in a strategic market management by a normal individual is based upon estimation of weight of single associated parameter and hypothesis of fairness by pessimistic individual is rejected, then for unit negative bias, the estimate of weight of the single parameter by either historical or predictive means by a normal person is represented as a complex variable.
2. Accuracy estimate of future prediction of occurrence of an uncertain event (gain or loss) is governed by the principle of hypothesis of fairness rule in case of both optimistic and pessimistic individuals.
3. In case of sales and profit estimation of strategic market management done by a fickle-minded person, the predicted value (Tv) clearly acts as a reference parameter for identifying the output (To) trends towards both rare and frequent fuzzy domains.
4. The null hypothesis of validity of an unknown event (gain or loss) for a biased individual is identical to alternate hypothesis of the same for a normal person.

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