Decision Support System Based Markov Model for Performance Evaluation of Students Flow in FCIT-KAU

Dr. Abdul Fatah Suliman Mashat,
Prof. Dr. Abdul Hamid M. Ragab, Ahmed M. Khedra
Faculty of Computing and Information Technology, KAU, Jeddah, S.A.
asmashat@kau.edu.sa, ahm_ragab@yahoo.com , ahmedkhedra@gmail.com

Abstract- This paper proposes an effective decision support system based on an absorbing Markov, which is used for helping decision makers in Faculty of Computing and Information Technology(FCIT) at King Abdul Aziz University (KAU) in controlling student's flow transition enrollment. Several important controlling criteria that govern student's flow performance during semesters are evaluated. These include estimating students flow between deferent study levels, the average life time a student spends at each level, the semesters required for graduation, and students graduating probability. A complete performance evaluation comparison between boys and girls at IT College is investigated. Results show that girls achieved better performance than boys. The system has several advantages, such as, helping to find any bottle necks to be solved during students transition study from one semester to another, and helping to know students needed facilities to planning for future required resources, hence achieving good quality and efficient university education.

Keywords- DSS, Markov Models, Students Flow Evaluation, Absorbing Markov Chain.

I. INTRODUCTION

Nowadays, interactive computer-based decision support systems (DSS) are very powerful technologies for solving complex decision making problems. These DSS systems are based on using knowledge theorems covers many diverse areas such as database research, artificial intelligence, decision theory, economics, cognitive science, management science, and mathematical modeling, as described in Table1. The main decision making unit in all sort of DSS systems usually use an analytical based model [1-6]. In the new FCIT College at KAU, the problem of understanding and assessing the flows of students through the educational system is very important due to its continuous changing and the increasing amounts of data. This is due to the large number of controlled and uncontrolled student's related factors such as specialization, courses, gender, and others are involved in the educational process. In this paper, we propose a Decision Support System based Markov Model (DSS-MM) for performance evaluation of students flow in FCIT College at KAU. The Markov Chain is used to model such dynamic systems [7, 9-11], since; over the time; each student state is usually changes from one specific state to another. The case study that is investigated includes both girls and boys sections in the College.

II. LETIRATURE REVIEW

DSS systems are powerful technologies for complex decision making and problem solving. However, constructing an accurate and interpretable DSS for any domain is a challenge. These systems help decision makers for taking suitable decisions by interfacing with data, models and other knowledge on the computers. DSS systems applications, summarized in Table1, are developed using several technological approaches including simulation, heuristic rules, optimization, fuzzy rules, and artificial intelligence.
Markov models [7, 9-11] are fundamental effective approach widely used in various fields including many several applications, such as indicated in Table1. The problem of understanding and assessing the flows of students through the educational system is very important due to its continuous changing increased amounts of data. This is due to the large number of controlled and uncontrolled factors [11], such as specialization, courses, gender are involved in the educational process. In this paper, we propose a Decision Support System based Markov Model (DSS-MM) for performance evaluation of students flow in FCIT College at KAU. A Markov Chain is used to model such dynamical system. Since, each student state is usually changes to another over time. The case study includes both girls and boys.

III. DEVELOPMENT OF STUDENTS FLOW DSS MARKOV MODEL

The DSS system proposed is based on using absorbing Markov chain. A Markov chain [12-14] is a mathematical process that undergoes transitions from one state to another in a chain like manner. It is a random process characterized as memoryless:

© ICCIT 2012

the next state depends only on the current state and not on the entire past. This specific kind of "memorylessness" is called Markov property.

Table 1: Examples of DSS case studies.

Authors	Year	Approach	Application
H. Huang [1]	2011	Hierarchical Co-evolutionary fuzzy	Detecting Gamma ray Signals
Z. Liao [2]	2012	Artificial Intelligence Network	Environmental Emergency
J.R. Gonzalez [3]	2009	Optimization Analysis	Protein analysis structure.
I. Mahdavi [4]	2010	Simulation Analysis	Job shop manufacturing.
S.W.K. Chan [5]	2011	A text based Analysis	Financial sequence prediction
H. Shen [6]	2008	Markov Chain Analysis	IT Project Management
J. Barker [7]	2009	Hidden Markov Models and time series anomaly detection	Information Fusion
D. Papakiriako-poulos [8]	2009	Heuristic Rules Analysis	Detecting products missing from a shelf
L.M. Pl`a [9]	2004	Embedded Markov model	A sow herd Problems
S. S. Leu [10]	2011	Neural-Autoregressive Hidden Markov Model	Micro tunneling in installing new pipelines.
S. Al-Awadhi [12]	2009	Markov Model Analysis	Students Flow Performance
This Paper	2012	Absorbing Markov Chain	KAU Students Flow Evaluation

A Markov chain is a sequence of random variables X_1, X_2, X_3, ... X_n with the Markov property. The present state, the future and past states are independent. Formally:

$$\Pr(X_{n+1} = x | X_1 = x_1, X_2 = x_2, \ldots, X_n = x_n) = \Pr(X_{n+1} = x | X_n = x_n)$$

The possible values of X_i form a countable set S called the state space of the chain A state si of a Markov chain is called absorbing if it is impossible to leave it (i.e., pij = 1). A state of a Markov chain is absorbing if it is impossible to leave it (i.e. the probability of leaving the state is zero). And a Markov chain is absorbing if it has at least one absorbing state, and if from every state it is possible to go to an absorbing state (not necessarily in one step). In an absorbing Markov chain, a state which is not absorbing is called transient.

The main core component of the proposed DSS-MM system is the Markov base model. The Markov chain for this model is implemented based on seven distinguished rules for student enrolment in KAU, as we defined in Table2. They include seven student states, namely: Freshman (F), Sophomore (So), Junior (J), Senior (Se), Graduated (G), Dropped (D), and Not registered (NR) students. The model algorithm of the DSS system computes, the student's transition matrix, which consists of seven by seven states. Two of these seven states, G and D are absorbing states (i.e. impossible to leave state, or student stuck state). This means that, once a student reaches the Graduated status, the student never leaves that state. The other five states: F, So, J, Se, and NR are student's transient states. The model algorithm will compute several other matrices that are related to number of students in each state for both boys and girls sections. Forecasting analysis related to student's flow are also carried out. Let us assume a student's progress through FCIT can be viewed as progression from state to another. The state transition diagram for students flow from one state to another can be represented as shown in Fig.1. The rules that govern these transitions are indicated in Table2. Where, X denotes the number of credit hours. R1-to-R7 defines the rules of student's transition flow from a specific current state to another one

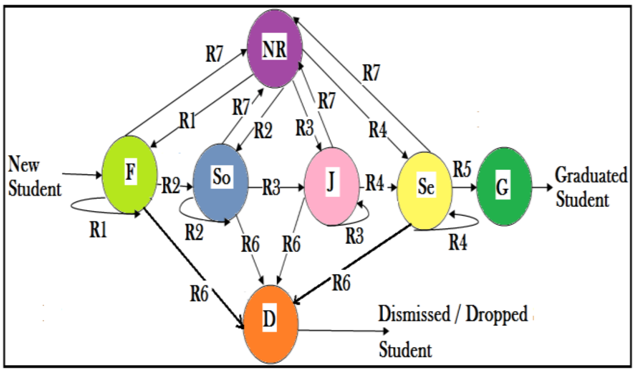

Fig.1: State Transition Diagram for Students flow.

Eventually the students progress to the graduated state (G), although it is possible that some students may drop out and never graduated. A student can be a freshman (F) student for one or several terms and then switch to not register (NR) status or can take a sophomore (So). Generally, probabilities of students switching from one state to another will be estimated by analysis their appropriate historical records. Historical frequencies can be then converted into relative frequencies, and these relative frequencies can be treated as transition probabilities between various states. When presented in a matrix form, these probabilities will provide the required transition matrix, which is used to estimate student's performance, as explained next.

Table2: FCIT Student Status and Rules related to Credit hours X.

States	Rules	Symbols
Freshman (F)	X <= 26	R1
Sophomore (So)	26 < X <= 60	R2
Junior (J)	60 < X <= 90	R3
Senior (Se)	90 < X < 140	R4
Graduated (G)	X = 140	R5
Dropped out (D)	Dropped out or Dismissed from FCIT	R6
Not Rejected (NR)	Not registered, due to personal problems, but eventually he will return to the system.	R7

A. Students Data Collections and Analysis

For the purpose of this paper, Students data is obtained from the FCIT College database at KAU. This data cover the period from the fall semester of the academic year 2006-2007 to the fall semester of the academic year 2011-2012. A student in the FCIT should complete 140 credit hours in about 12 semesters to be graduated. A Markov chain of 7 states is identified and records of 221 students are examined. Each state is classified as illustrated in Table 2. Two of these five states, G and D are absorbing states. Once a student reaches the "Graduated" status, a student never leaves that state. If a student has permanently dropped out or withdrawn from College, the student continues to be in state D. The other five states: F, So, J, Se, and NR are transient states. If the process is in one of these states, there is a probability that the process will never return to that state.

B. The Frequency of Student Transitions

The transition matrix for the seven by seven state Markov chain will take the form shown in Table 3. It illustrates that states G and D are absorbing states, while the other states are transition states. Table3 also shows the number of student's transitions from one level to another. For example, the number of So students who transferred to J level is 210.

Table 3: The Transition Frequency Data Matrix (TFDM) of 221 male students in FCIT.

To / From	F	So	J	Se	G	D	NR	total
F	455	8	0	0	0	7	226	696
So	0	241	210	0	0	2	135	588
J	0	0	133	117	1	2	24	277
Se	0	0	0	455	582	0	82	1119
NR	24	201	132	0	0	0	0	357

We formulate the canonical form of the probability matrix P as indicated in Table 4. For an absorbing Markov chain, renumber the states so that the transient states come first. If there are r absorbing states and t transient states, the canonical form of transition matrix P will have the following form:

$$P = \left[\begin{array}{c|c} I & 0 \\ \hline R & Q \end{array}\right] \quad \ldots\ldots\ldots (1)$$

Where, I is an identity matrix, I= r x r, O = r x t (zero matrix), R is matrix of transition probabilities from transient states to absorbing states and R= t x r. The matrix Q is the transition probabilities between transient states and Q= t x t. Table 4 shows the canonical form of transition probability matrix (P) for 221 male students during 16 semesters, starting from year 2006. Table 4 shows also the transition probability matrix (Q) for the male students in the 16 terms. The Q matrix is computed using data from TFDM by dividing the values corresponding specific cell into the value in the column total, for example the F value 0.654 is obtained by dividing 455 / 692.

Table 4: Canonical form of transition probability matrix P.

		I		O				
	To / From	G	D	F	So	J	Se	NR
	G	1.000	0.000	0.000	0.000	0.000	0.000	0.000
	D	0.000	1.000	0.000	0.000	0.000	0.000	0.000
P =	F	0.000	0.010	0.654	0.011	0.000	0.000	0.325
	So	0.000	0.003	0.000	0.410	0.357	0.000	0.230
	J	0.004	0.007	0.000	0.000	0.480	0.422	0.087
	Se	0.520	0.000	0.000	0.000	0.000	0.407	0.073
	NR	0.000	0.000	0.067	0.563	0.370	0.000	0.000
		R		Q				

IV. SYSTEM REALIZATION AND RESULTS DISCUSSION

The system will manipulate the frequency data matrix shown in Table3, which contains student's numbers and their states. Then, it generates other matrices, such as the fundamental matrix N, which can be used for computing the graduating, dropping and ending probabilities. Forecasting students future enrollments based on their current enrollments are estimated using matrix M and U. Then, Comparison between girls and boy's student's flow will also be investigated. Fig.2 shows the computing steps followed by the algorithm.

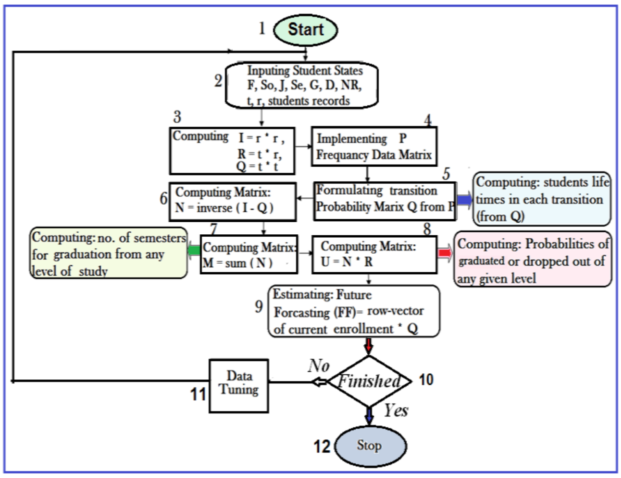

Fig.2: DSS Markov Model Computing Flowchart.

A. Estimating Students Flow between Deferent Levels

The transition matrix Q shows the probabilities of students flow from one specific level to another. To understand the meaning of the values of the seven-by-seven transition matrix of probabilities in Table4, let us consider a randomly-selected student who happens to be on not register (NR) state at present. The probability of that student returning to freshman student status (F) is 0.067 (which is about 7%), while the probability of switching to sophomore status (So) is 0.563 (which is about 56%) and the probability of to be junior (J) is 0.370 (which is about 37%). Hence, we estimated, for example, the probability of a freshman student to remain freshman is 0.654 (about 65%), while the probability to become not registered is 0.325(i.e. about 33%), and the probability to be sophomore is 0.011 (i.e. about 1%). Similarly, the probability for sophomore, junior, and senior students to remain in the same level are 41%, 48%, and 41%, respectively.

B. The Average Life time a Student Spends at Each level

To estimate the life time that a student spend at any level, we need to construct the fundamental matrix N; where N = inverse of [I-Q]; for the 16 terms. For an absorbing Markov chain P, the matrix $N = (I-Q)^{-1}$

It called the fundamental matrix for P. The entry nij of N gives the expected number of times that the process is in the transient state sj if it is started in the transient state si. By formulating both the matrix I and matrix Q from the matrix P shown in Table4, we get the N matrix shown in Table5. The main diagonal of the fundamental matrix N shows that the student needs, on the average, about 3 semesters to finish the requirements of freshman, sophomore, or junior. Finally the student can finalize the senior, or not register level in approximately 2 semesters.

Table 5: the fundamental Matrix N for 16 terms

To / from	F	So	J	Se	NR	Total rows (M)
F	3.240	1.794	2.523	1.796	1.814	11.167
So	0.203	2.695	2.595	1.847	1.045	8.385
J	0.098	0.485	2.617	1.863	0.507	5.571
Se	0.045	0.224	0.321	1.914	0.234	2.739
NR	0.368	1.818	2.598	1.850	1.898	8.532

C. The Semesters Required for Graduation

Table 5, shows the vector M that its components represent the average number of changes of the state for the original process. It is computed by summation of each cell value in the rows. This summation represents the required number of semesters that a student spends to be graduated. We see from Table5 that a freshman student stays on the average about 11 semesters in the system before reaching an absorbing state, while sophomore and not register student stays about 8 and 9 semesters, respectively. Also junior student needs about 6 semesters, while a senior student needs about 3 semesters to reach one of the absorbing states.

D. The Students Graduating Probability

We use the matrix U which indicates the probability that an amount in one of non-absorbing states will end up in one of the absorbing states. The matrix U is computer as U = N*R. The matrix R is shown in Table4 and the matrix N is shown in Table5. Table 6 shows the computed matrix U. It indicates probabilities of semesters required for graduating starting from any level of the study. The top row of U matrix indicates the probabilities that freshman student will end up in the graduate and drop out category. It also shows that freshman student has a probability of 94% of progressing to be graduated (progress to state G) and a probability of 6% of progressing to the state D ,while a sophomore and a not registered student have a probably of 97% to be graduated (progress to state G) and a probability of 3% of progressing to the state D. Also U matrix shows that about 2% of the junior student get absorbed to sate D (withdraw or dropped out of the system).

Table 6: the computed matrix U.

	G	D
F	94%	6 %
So	97%	3 %
J	98%	2 %
Se	100%	0 %
NR	97%	3 %

E. Comparison Between Boys and Girls Performance

The algorithm followed above is used also to estimate girls flow performance at the IT KAU College. The complete results of the performance evaluation are shown in Table 7. From these results, it is clear that girls achieved better flow performance than boys.

Table 7: Comparison Between Boys and Girls Performance.

Evaluated Parameters	Life time Students spend at each level				Semesters Required for Graduation				Graduating Probability From any Level			
Category	Girls Probability		Boys Probability		Girls Semesters		Boys Semesters		Girls		Boys	
Levels	Estimated Value	Rounded Average	Estimated Value	Rounded Average	M	Rounded Average	M	Rounded Average	G	D	G	D
F	2.790	3	3.24	3	9.678	10	11.167	11	97%	3%	94%	6 %
So	2.271	2	2.695	3	9.028	9	8.385	8	98%	2%	97%	3 %
J	2.141	2	2.617	3	7.496	7	5.571	6	99%	1%	98%	2 %
Se	2.348	2	1.914	2	3.481	3	2.739	3	99%	1%	100%	0 %
NR	2.429	2	1.898	2	7.599	8	8.532	9	99%	1%	97%	3 %

V-CONCLUSION

This paper proposed an effective decision support system based on an absorbing Markov chain. It can be used effectively as a computerized decision making tool for helping decision makers at KAU. The system can be used for estimating students flow performance using several important criteria such as, student's transition flow between deferent study levels, the average life time a student spends at each semester, the semesters required for graduation, and students graduating probability. A complete performance analysis comparison between boys and girls at IT College is investigated. Results showed that girls achieved better performance than boys. The system achieves many other advantages, among which, it helps to find and solve any sort of bottle necks during student's transition from one semester to another. It also helps to know students needed facilities to planning for future required resources, hence achieving good quality and efficient university education.

ACKNOWLEDGMENT

Authors would like to thank Mr. Mahmod Alsehetry, and IT deanship at KAU for offering us students data used in this paper.

REFERENCES

[1] H. Huang, M. Pasquier, C. Quek., "Decision Support System based on Hierarchical Co-evolutionary Fuzzy approach: A case study in detecting gamma ray signals", Expert Systems with Applications, V(38) , Issue 9, pp 3626-3631 ,September 2011.

[2] Z. Liao et al., "Environmental emergency decision support system based on Artificial Neural Network", Safety Science, V (50), Issue 1 ,pp150–163, January 2012

[3] J. R. Gonzlez *, D. A. Pelta, A. D. Masegosa , "A framework for developing optimization-based decision support systems,, Expert Systems with Applications", V(36), Issue 3, Part 1, pp 4581–4588, April 2009.

[4] I. Mahdavi , B. Shirazi, M. Solimanpur, "Development of a simulation-based decision support system for controlling stochastic flexible job shop manufacturing systems", Simulation Modeling Practice and Theory, V(18), Issue 6, pp 768–786. , June 2010.

[5] S.W.K. Chan , J. Franklin ,"A text-based decision support system for financial sequence prediction", Decision Support Systems., pp 1-10, , July 2011.

[6] H. Shen , R. G. Qiu , Jidi Zhao, "A Group Decision-Support Method for IT Project Management Based on Markov Chain" , IEEE Inter. Conf. on Systems, Man and Cybernetics ,SMC 2008.

[7] J. Barker et al., "Information Fusion Based Decision Support via Hidden Markov Models and Time Series Anomaly Detection", 12th International Conference on Information Fusion, Seattle, WA, USA, July 6-9, 2009.

[8] D. Papakiriakopoulos, K. Pramatari, G. Doukidis., "A decision support system for detecting products missing from the shelf based on heuristic rules" , Decision Support Systems, V(46), Issue 3,pp 685–694, Feb. 2009.

[9] L.M. Pla, C. Pomar, J. Pomar " A sow herd decision support system based on an embedded Markov model, Computers and Electronics in Agriculture ", V(45), Issues 1-3, ,pp 51–69, December 2004.
[10] S. Leu, T. Adi, "Micro tunneling decision support system (MDS) using Neural-Autoregressive Hidden Markov Model, Expert Systems with Applications", V(38), Issue 5 , pp 5801–5808, May 2011.
[11] G. Koua , Y. Shib , S. Wangd, "Multiple criteria decision making and decision support systems- Guest editor's introduction" ,Decision Support Systems, V(51), Issue 2,pp 247–249, May 2011,
[12] S. A. Al-Awadhi and M.R. Konsowa ,"An Application of Absorbing Markov Analysis to the Student flow in an Academic Institution, the 1st Arab Statistical Conference, Amman, Jordon, Nov., 2007.
[13] N. K. Kwak, R. Brown and M. J. Schiederjans , "A Markov analysis of estimating student enrollment transition in a trimester institution" , Socio-Econ. Plan. Sci., Vol. 20, No. 5, pp. 31I-318, 1986.
[14] J. Mo, "Performance Modeling of Communication Networks with Markov Chains" , Morgan & Claypool, Vol. 3, No. 1 , pp 1-90 ,2010.