A PROTOTYPE FOR EDUCATIONAL PLANNING USING COURSE CONSTRAINTS TO SIMULATE STUDENT POPULATIONS

Sep 30, 2008

Thanassis HADZILACOS^{1,2}, Dimitris KALLES^{1,3}, Dimitris KOUMANAKOS⁴, Vasilios MITSIONIS³

¹Open University of Cyprus, Nicosia, Cyprus

²Research Academic Computer Technology Institute, Rio, Greece

³Hellenic Open University, Patras, Greece

⁴Department of Mechanical and Aeronautical Engineering, University of Patras, Rio, Greece

Contact: kalles@eap.gr

ABSTRACT

Distance learning universities usually afford their students the flexibility to advance their studies at their own pace. This can lead to a considerable fluctuation of student populations within a programme's courses. The evolution of the student population may be an important factor in determining the academic viability of a programme as well as the resources that have to be budgeted and administered. Providing a method that estimates this population could be of substantial help to university management and academic personnel. We describe how course precedence constraints are used to calculate alternative tuition paths and we then use Markov models to estimate future populations. In doing so, we identify key issues of the potential deployment of such a system at a large scale.

KEYWORDS

Simulation, population estimation, precedence constraints, educational planning.

1 Introduction

Distance learning universities usually afford their students the flexibility to advance their studies at their own pace. This can lead to considerable fluctuation of student populations within a programme's courses, possibly affecting the academic viability of a programme as well as the resources that have to be budgeted and administered. Providing a method that could guide management and academic

personnel towards estimating this population could be of substantial administrative value (Chang and Radi, 2001; Webster, 1997).

Such fluctuations also occur in the Hellenic Open University¹ where students⁷ personal circumstances may easily change within short periods, mostly due to family and employment reasons. Moreover, as in most similar universities (Open Learning, 2004), significant drop-out rates are recorded in some programmes, usually as a result of failure in a junior year. While understanding and addressing the reasons of failure is an educational problem, drop-out also amplifies the administrative consequences of unexpected fluctuations in the student population.

In HOU, administrative aspects that are mostly affected by the student population include tutor contract renewal, tutoring venue rental and allocation, the procurement and distribution of educational material, and the development and operation of (mostly IT) infrastructure. As only about 15% of HOU running costs are provided by the government and the rest is borne by students, cost consciousness is essential during planning and before taking decisions, especially so if one might consider venturing into several-year contracts.

In this paper we present a method to estimate student populations based on course precedence constraints, as stipulated by programme regulations. These constraints are used to calculate alternative tuition paths for students, based on data about past enrolments and exam successes (note that no individual records are examined).

The rest of the paper is structured in six sections. We next offer some more details on the educational setting at HOU, mainly to introduce the associated nomenclature. We then present the specification, its implementation and its results, in three subsequent separate sections. Following that, we identify the issues that we need to resolve before we field our approach at a larger scale. Finally, while concluding, we also briefly reflect on the political aspects of using simulation for educational planning.

2 Background on the Educational Application Field

In this work we have focused on a Master's conversion programme in Information Systems offered at HOU. Students have the opportunity to acquire specialized knowledge in Information and Communication Technologies, and to prepare for professional work in the design, development and management of integrated information systems. The programme is targeted at science and engineering graduates and covers the design and development of software and systems, the management and the quality of system development, and advanced issues in telecommunications and networking. It offers five taught modules, four of which must be completed to proceed to a thesis. Of those modules, one is a compulsory and demanding introduction to the programme with recorded success rates of about 50-70% and drop-out being the usual path after failure.

¹ HOU was founded in 1992 and offered its first courses in 1998. Currently, over 25,000 (mature) students are enrolled and over 1,500 tutors are active on a yearly basis.

A module is the basic educational unit at HOU. It runs for about ten months and is the equivalent of about 3-4 conventional university semester courses. A postgraduate student may register with up to two modules per year. For each module, a student is expected to attend five plenary class meetings during the academic year. A typical class contains about ten to thirty students (depending on geographical distribution) and is assigned to a tutor. All tutors of classes of the same module collaborate on various module aspects. Class meetings are about four hours long and are structured along tutor presentations, group-work and review of homework. Furthermore, each student must turn in some written assignments (typically four or six), which contribute towards the final grade, before sitting a written exam.

Students may not sit the written exam if they do not achieve a pass grade in the assignments they turn in; these students must repeat that module afresh. A student who only fails the written exam may sit it on the following academic year; such students are also assigned to student groups but the tutor is only responsible for marking their exam papers and they are not obliged to turn in homework.

In earlier studies, Xenos *et al.* (2002) reported that undergraduate students who dropped out usually claimed that they were not able to correctly estimate the time that they would have to devote to their professional activity and, as a result, the time dedicated to their education decreased unexpectedly. Some also felt that their knowledge was not sufficient (other reasons, such as family or health issues were also quoted). Our experience with a demanding postgraduate programme confirms these findings.

We have to date also invested on a separate *bottom-up* research direction to analyse students' performance in various modules, based on assignment and exam data (Kalles and Pierrakeas, 2000a, 2000b; Hadzilacos *et al.*, 2006; Kalles *et al.*, 2008). In this paper, however, we describe a *top-down* approach that aims to estimate student populations based on historical enrolment data; eventually we will attempt to demonstrate that the two approaches are complementary. To put it in a nutshell, we believe that educational intelligence must be built upon data drawn from various sources and at varying resolutions (bottom-up); it is then up to academic personnel to integrate the views and exploit the findings with concrete decisions (top-down).

It is interesting to note that the methodology developed in this paper was first conceived to address the problem of estimating the number of students in the programme, so as to better argue about increasing the number of students that can be admitted at registration. Such a direction would not be easy to explore unless one has a solid appreciation of the demand for the programme as well as an appreciation of the potential availability of suitable tutoring personnel.

3 Specification of the Simulation

A simulation starts by specifying the state space and the state transition probabilities. Before presenting the details of the representation, we first describe the application domain and then offer a brief overview of the simulation workflow.

The programme consists of five taught modules, as shown below with their respective code:

- pls50: Fundamental Specialization in Theory and Software

- pls51: Fundamental Specialization in Computer Architecture and Computer Networks
- pls60: Specialization in Software Engineering
- pls61: Software Design and Management
- pls62: Specialization in Networks and Communications

Modules 50 and 51 are junior modules and are compulsory. Modules 60, 61 and 62 are senior modules and any two of them may be selected towards the degree, which must contain four taught modules. A student may attend at most two modules per year; when four modules are successfully completed, the student may proceed to a final year thesis. There are some precedence constraints, namely:

- Module 50 must be successfully cleared before enrolling in either of modules 60 and 61.
- Module 51 must be successfully cleared before enrolling in module 62.
- Enrolment in any senior module cannot be prior to enrolment in any junior module.

There is an extra regulation that effectively guides students towards the "foundation" module of this programme: ²

- Module 50 must be the first to be selected.

Moving from registration to graduation can then be cast as a search problem, where any legal path from a start state (registration) to an end state (graduation or drop-out) is a sequence of module enrolment sets, with each set denoting an academic year. Modules can appear along more than one such consecutive set to account for failure and re-attendance. The details of how one can formally describe the precedence constraints of modules and how such precedence constraints can be generated from rules like the ones enumerated above are presented in sections 3.1 and 3.3 (note that, whereas the first section 3.1 deals with the problem of how to represent the possible paths a student takes, section 3.3 deals with how to generate those representations automatically; effectively, we are also addressing a meta-modelling problem with our methodology).

While understanding the individual tuition paths may be an interesting educational problem, a simple enumeration does not offer any insight into how populations evolve. Our approach is to simulate the individual legs of each one path, allowing for a probabilistic decision at each point in (simulated) time on what action to take next. We thus make use of our knowledge of available options and we harness university enrolment data to calculate the transition probabilities. This is detailed in section 3.2.

3.1 Drawing the State Space Graph

A state is the set of modules that a student has selected at an academic year (all selected modules up to that point). A transition between states is the selection of modules for the current academic year.

² We refer to the term "foundation" essentially denoting a module within the programme that helps focus students on the study domain. Some HOU programmes have more than one foundation module and may either enforce similar regulations, or simply issue recommendations.

That way, we can model the path that a student follows while enrolled for the particular program, where each state represents an academic year and state transitions represent the module registration actions that occur at the start of each academic year.

According to these conventions, the state space for the programme we are examining is shown in Figure 1 (transition probabilities are not shown yet, to avoid cluttering).

A few notes on nomenclature are due. Numbers indicate module codes (50, 51, 60, 61 and 62). An italicised number annotating a transition line conveys the information that the transition happens upon selection of the particular module (or, modules). As an example (following the dashed lines), note that a student may have registered for module 50 for the first academic year, then moved on to select modules 51 and 60 and finally registered for module 62 for the third year, thus taking three years to move from a start to a sink state (both shown in bold). We consider *state:50,51,60,62* (and its two siblings) as sink states because the master's thesis that follows it must be carried out independent of any module attendance obligations.

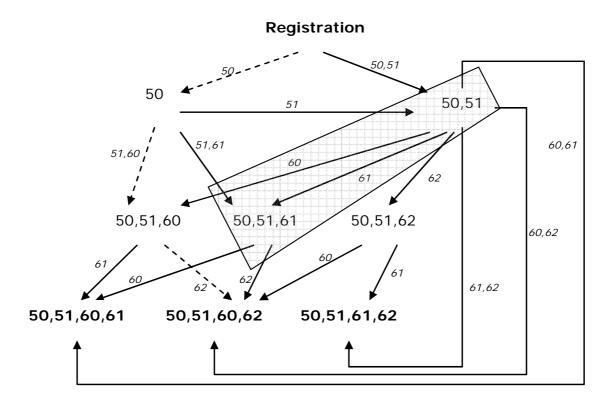


Figure 1: The state space of module enrolments.

Note that the model in Figure 1 is not totally complete, since it must be enhanced with transitions from every state to itself (to account for failing a module or a combination of modules and having to repeat it), as well as with transitions from every state to a sink state (to account for those students who drop out of their studies). Such extra transitions, however, do not really add to the comprehensibility of the model and we do not show them to avoid cluttering.

The model in Figure 1 uses transition labels to convey information on which courses a student is currently attending. We have eventually used a more verbose notation, which nonetheless is easier to comprehend by humans as regards course selection (and is more expressive as well). For example, note that what used to be *state:50,51,61* in Figure 1 (in the trapezoid section) has now been broken up in two states (see right part of Figure 2), increasing the number of transitions fanning out from (what used to be) *state:50,51*. The new notation uses a *dash* (-) to separate completed modules from currently attended modules. So, with reference to Figure 2, we note that a student who has completed module 50 and is currently attending module 51 (see top state) may fail and simply repeat module 51 (left branch), or may also further register for module 61 (middle branch), or may be successful and register for module 61 only (note that there exist more edges from that state, but we omit them; we just need to convey the concept).

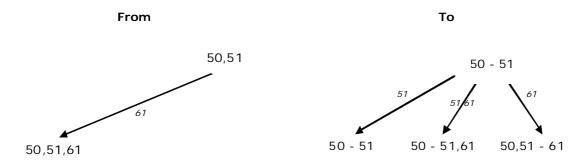


Figure 2: A verbose variant of the visual model of precedence constraints.

3.2 Calculating the State Transition Probabilities

For our prototyping experiment, the specification of the transition probabilities was based on the statistics of the first two years of the programme's running³. For the senior year modules, where data on success and failure were not available, we substituted default values based on our tutoring experience (that senior year students are very unlikely to fail).

Figure 3 shows a snapshot of the transition probabilities for the state space of our model (using the initial, dense, representation).

_

³ The programme was first offered in 2004-5. We used the enrolment and examination data of that year and the enrolment data of 2005-6, examining all individual student records, to calculate the transition probabilities (rounded at multiples of 0.05). As of 2006-7, the intake increased from 120 to 150 students per year. See Section 6 on how our approach may be affected by such a fluidity of the educational context in a real field deployment.

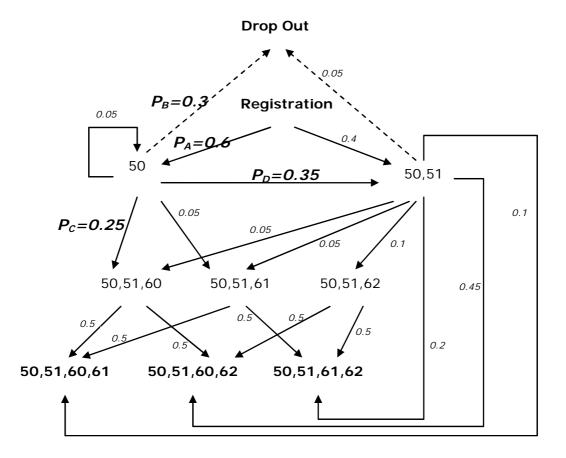


Figure 3: A snapshot of the transition probabilities of module enrolments.

Probabilities P_{A} , P_{B} , P_{C} and P_{D} (shown in larger font) initially seemed to mostly affect the simulation and they corresponded to the most easily observable student paths in the programme:

- At the outset of the programme, a student may start with enrolling either in module 50 or in modules 50 and 51. The probability to only select module 50 is P_A .
- There is a relatively high probability to fail module 50 and to drop out altogether subsequently, P_B.
- A successful completion of module 50 is followed by an obligatory enrolment in module 51 and an optional enrolment in a second year unit, usually module 60.
 - o The probability to select those two modules is P_C .
 - The probability to select just module 51 is P_D .

Zero transition probabilities are not shown but there are plenty of them (for example, drop-out at senior modules). Also, all other transitions from any state were assigned default probabilities, by subtracting all probabilities that reflected the special cases, by allowing for a small drop out probability at some senior units, and by assigning rounded values based on the actual statistics of the previous real population. Where we had no reason to select one between two alternatives, a default value of 0.5 was specified.

3.3 Using a (Visual) Grammar to Generate the State Space Graph

For the postgraduate programme we are studying, where five taught modules are offered and four of them must be completed to proceed to a thesis, the eventual state space consists of several dozens of states and transitions. As the full representation for a programme must account for a range of possibilities on selecting more than a module per year, on deciding the order of module selection (when that is an option), or on deciding which optional modules to select (essentially, just like how Figure 1 was produced), it follows that representation size may scale into hundreds of elements for a programme of several modules (as is typical for undergraduate programmes in HOU).

At such a model size, the complete specification may be simply unmanageable to draw and the process is prone to errors. A reasonable extension is a modelling notation that captures the precedence constraints between modules and can automatically generate transitions.

Instead of introducing that notation formally, we use Figure 4 as an example that shows the visual graph model for our programme.

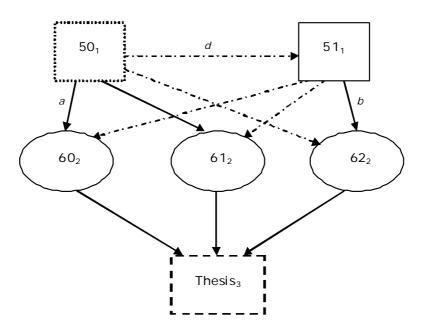


Figure 4: A high-level visual model of precedence constraints.

Therein, numbers indicate module codes and subscripts indicate the nominal year of the programme where a module has been allocated. Edge indices denote precedence constraints (see Table 1 for reference but also note that only a couple of them are shown to avoid cluttering). A solid edge indicates a hard precedence, in the sense that a module cannot be selected (for enrolment) unless its precedent has been completed. A dashed edge indicates a soft precedence, in the sense that a module cannot be selected unless its precedent has at least started. A rectangle indicates a compulsory module; an oval indicates an optional one. A dotted module must be among the first where the students enrol (as is the case with foundation courses); a dashed module must be among the last where the students enrol (as is the case with theses). When an optional module is shown as a

precedent to another module, the semantics is that in the final selection of modules, the antecedent may not appear before the precedent (but the precedent may be missing and so will be the antecedent).

Table 1. List of constraints (precedence constraints are indexed)

# constraint	Description
	50 is compulsory
	51 is compulsory
	60 is optional
	61 is optional
	62 is optional
	A Thesis is compulsory
а	50 must be successfully cleared before enrolling in either of modules 60 and 61
b	51 must be successfully cleared before enrolling in module 62
С	Enrolment in any senior module cannot be prior to enrolment in any junior module
d	50 must be the first to be selected
E	A thesis is only available as the last module

A key advantage of the above notation is that it is easy to communicate to users who are non-versed in such formalisms. While one may not readily request that they produce the model, it should nevertheless be straightforward to convince them about its correctness because, since precedence constraints can be derived from university regulations, there is no room for subjective interpretations. This could help address a certain reservation towards formalisms that is sure to be exhibited among many of our colleagues, particularly those of the humanitarian disciplines.

We have used Prolog to implement the model for our programme. The basic code block implements a topological ordering to generate all admissible tuition paths of four modules (as required to proceed to a thesis). ⁴ Essentially, on input of a specification as shown in Figure 4, a graph is output where nodes are sets of selected units and edges are transitions between states, as shown in Figure 2. The output can be edited and then visualized with *Graphviz*⁵ or similar visualization software.

⁴ Note that an edge in Figure 4 may in fact satisfy more than one constraint, as is the case, for example, for the edge between modules 51 and 62 (it also satisfies constraint c). In these cases we only show the stronger constraint. Note, also, that some edges are redundant as is the case, for example, for the edge between modules 50 and 62 (which is redundant due to the edges indexed d and b). In either case this extra information may be included in the graph model for the sake of completeness; any reasonable implementation will prune multiple occurrences of the same tuition path down to one.

⁵ Graphviz is available at http://www.graphviz.org.

Further specifications can be straightforward accommodated in the above model, but one could also opt to develop a modelling extension instead. For example, some programmes may demand that a module may not be selected unless all previous year modules have been selected. While, in Figure 4 this has been captured on a module-by-module basis, one could represent this constraint at a higher level (Figure 5).

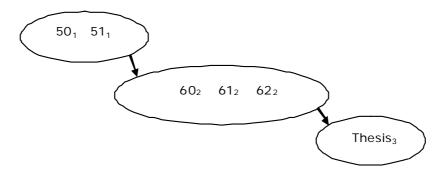


Figure 5: A simple extension of a high-level visual model of precedence constraints.

To avoid complicating the modelling notation we have opted to embed some further constraints in the Prolog code, since they do not interfere with the conceptual aspects of the model (such are the constraints about allowing students to enrol in at most two modules per year and about requiring four modules to advance to a thesis, both of which are not captured in Figure 4). A similar modelling problem refers to denoting which modules must come either first or last; we have opted to embed these constraints in the fundamental notation (see the dotted and dashed modules in Figure 4).

4 Implementing the Simulation

Our implementation approach was two-pronged: one via commercial discrete simulation software and one via home-grown Markov model calculations (integrated in the software).

4.1 Using the Extend system for Simulations

We first used the *Extend*⁶ simulation software to code the discrete simulation experiment. The Extend software belongs to the visual programming genre where the programmer selects from a library of modules (components, functions) and creates flows between them; these flows then serve as pathways for discrete simulation objects (simulated students in our case) to move around into the simulated system. Figure 6 shows a snapshot of the Extend code that implements our experiment; we note that the shown extract accounts for about one-fifth of the overall program.

To briefly guide the reader around the Extend concepts, we coarsely describe some graphical programming elements (from left to right with reference to Figure 6), but note that this is simply meant to give an appreciation of the concepts and not to explain the implementation. We first note two

⁶ Extend is available from http://www.imaginethatinc.com/.

lines of objects running parallel to each other (L_1 and L_2) that mostly contain the simulation logic in terms of randomized experimentation, look-up tables for transition probabilities, etc. (other parts of the code demonstrate such structure as well). Immediately to the right of those visual structures one can see a vertical group of about a dozen rectangular blocks; these are object counters which tally the number of (simulated) students arriving at a particular state of the state space graph. Note that the output of such a block (see the arrowed lines for an example) is directed to a log file (rightmost column of three elements) and to a state to serve as input for the next time unit (year).

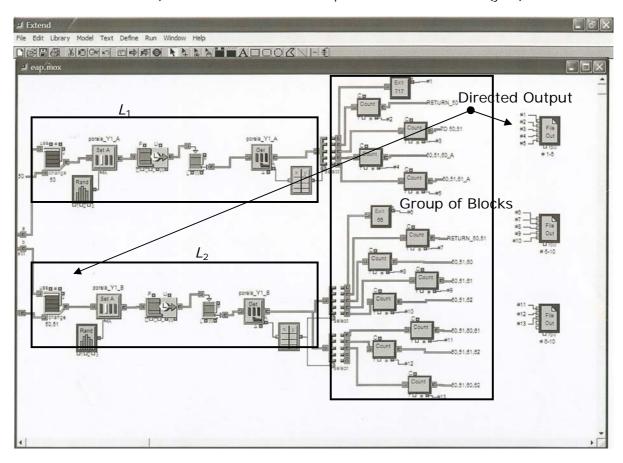


Figure 6: A snapshot of the Extend code that implements our experiment.

Extend works by using the above visual programming elements to implement the state space. Subsequently, it generates a number of simulated students and sends each one of them along a particular path, where at each state a probabilistic decision is made on which state to visit next. Eventually, such a simulated student arrives at a sink state (expected graduation or drop-out). Students are tallied at all states and then module populations are calculated based on the sum of the populations that have been reported wherever that module appears in the label of state.

Ease of implementation is a significant issue to ponder when one deals with such software. While conducting our first experiments with Extend it became glaringly obvious that we were facing a new variant of the problem that led us to develop the grammar described in Section 3.3 to minimize the verbosity of the original specification that would be daunting to check and verify. The final size of an

Extend implementation and the repetitive nature of the Extend code when applied to this problem are both conducive to allowing implementation errors to creep in.

The apparent challenge, now, was to directly generate Extend code excerpts and their interconnections by only using as input the visual grammar. In such a setting, we would still need to populate graph edges with transition probabilities but, even if we eventually opt to not enhance the grammar with probabilities, it would be far easier to fill such probabilities in predefined *blanks* in the generated code excerpts, especially so if we also decide to use default values for most of the transitions.

4.2 Integrated Simulation via Markov Chains

Drawn from the understanding that the Extend approach might not be scalable⁷ for our problem, we opted to use Markov chains to implement the calculations that estimate the student populations based on the transition probabilities, instead of simulating *each* student separately.

The key tool from the Markov chain toolbox (Grinstead and Snell, 1997) is the formula $v^n = v^{n-1}P = v^1P^n$ that allows us to express the population at some states (v is a state vector) as a function of the transition probabilities matrix (P) over a period of defined duration (n years, with each year counting as one step).

In our new implementation (Mitsionis, 2008), however, we also catered to some other improvements, all of which were largely unavailable in the Extend implementation:

- Each year accommodated a variable number of students being admitted to the program. We opted to not model this as a stochastic process but to simply allow the user to input a set of values, since (at least, in our case) it is usually university regulations that govern how many students will be eventually admitted.
- Transition probabilities cannot be accommodated in the visual model shown in Figure 4; a utility was developed to allow the user to fill-in the probabilities, while the probability matrix was automatically generated from the specification.

The new implementation also deals effectively with providing an integrated environment within which one can deal with these simulations. Specifically, a Visual Basic application (which can be viewed as a wrapper) was developed to capture (non-visually, however) the constraints as detailed in Section 3.3. These constraints were then used to generate the corresponding Prolog code that produces the alternative paths. The wrapper was then used to execute the Prolog code and to analyze its output, based on which it created the Markov chain representation of the simulation to follow. The simulation

⁷ At this point it is imperative to acknowledge that this decision also reflects a relative lack of advanced knowhow with the intrinsics of the *Extend* system. Indeed, we cannot rule out that a suitable compilation of programming techniques within *Extend* might offer a more cost-effective solution, but since we are also concerned with the potential take-up of our approach, we are keen to invest in techniques that demand a relatively smooth learning curve on behalf of prospective applicants.

then proceeds by inputting initial student data and by manipulating the transition probabilities. The output is calculated in two distinct way, one by conventional programming and the other by embedding the calculations into MS Excel, so that individual steps can be analyzed and followed-up by seasoned analysts who may want to look for details (MS Excel embedded calculations are quite more time-consuming, however).

5 Preliminary Simulation Results

We have conducted experiments with the above implementation to provide a proof of concept for estimating the student population of our postgraduate programme.

5.1 Discrete Simulation with Extend

With reference to Figure 3, which shows our fundamental assumptions for the transition probabilities, we note that with *Extend* we used *nine* configurations of these probabilities (P_A , P_B , P_C and P_D) which we thought would provide us with an initial appreciation of the variability of the population estimates. We developed these configurations *ad hoc* by focusing on the flow of students to and from the junior modules and we experimented with some fluctuations around the originally calculated values:

- At the outset, the probability to only select module 50 was set at $(P_A=)$ 0.6, 0.65 or 0.7.
- The probability to fail module 50 and to drop out altogether was set at $(P_B=)$ 0.5, 0.4 or 0.3.
- The probability to select modules 51 and 60 after module 50 was set at $(P_C=)$ 0.15, 0.2 or 0.25.
- The probability to select just module 51 after module 50 was set at $(P_D=)$ 0.25, 0.3 or 0.35.

Table 2 presents the probabilities of the nine configurations that we used; each one as a basis for a separate experimental session:

Table 2. Probability combinations for experimental batches

# Exp	P_A	P_B	P_C	P_D
1	0.60	0.50	0.25	0.15
2	0.60	0.40	0.30	0.20
3	0.60	0.30	0.35	0.25
4	0.65	0.50	0.25	0.15
5	0.65	0.40	0.30	0.20
6	0.65	0.30	0.35	0.25
7	0.70	0.50	0.25	0.15
8	0.70	0.40	0.30	0.20
9	0.70	0.30	0.35	0.25

Note that these values are not totally unrelated and there exist some combinations of values (shading and borders in Table 2 indicate areas of co-varying probabilities). The value of P_A is varied independently because this is the single most critical aspect that governs the student population before any studies are really commenced. We have seen that students of this programme are in general reluctant to take up a heavy workload and prefer to first "test the waters", especially so in the context of distance learning which they are totally unfamiliar with. On the other hand, the values of P_B , P_C and P_D co-vary because they reflect the expectation that a student who has enrolled only in one introductory module and failed it (P_B) , is increasingly unlikely to venture into further enrolments (P_C, P_D) before clearing that hurdle.

Admittedly, a detailed enumeration of all transition probabilities and/or an exhaustive combination of the above probabilities would lend more credibility to the overall experiment, as would the acknowledgement that, however small, a non-zero probability of failure is reasonable for senior modules too. However, our decision to carry out a smaller scale of experiments was coupled with combining those probabilities in a way that would allow the simulation to produce larger differences in the estimated populations, thus also allowing us to obtain some insight into the robustness of the estimates and the qualitative aspects of the insight that they might offer us. So we judged that our proof of concept attempt would not greatly benefit from more experimentation.

Each one of the nine configurations was used as an input to an experimental batch that simulated 20 academic years with 120 new students enrolling each academic year. We then averaged the simulated populations enrolled in each module for these years and report the averages. Since we report all experiments together, we have opted to not include deviations in our results to avoid cluttering; still, one should be able to derive from the presentation of quite different experiments that deviations within a single experiment would have to be smaller than differences across experiments.

We now show some evidence that the above introduced probability fluctuations help one gain a basic understanding of the population dynamics. Of course, they mostly serve as proof of concept and, in an operational context, an *ad hoc* selection of experimental configurations will not suffice. This is a task that has to be meticulously designed and carried out, using, for example, standard sampling techniques (Iman *et al.*, 1981), if one is to use the estimated populations for strategic planning.

The estimated populations are shown in Table 3:

Table 3. Estimated student populations per module

#	Ехр	50	51	60	61	62
	1	156	68	61	28	51

_

⁸ It is very interesting to note that for the corresponding undergraduate programme it is difficult to convince prospective students to **not** take up too much workload. This observation and the discussion in section 6 serve as cautionary notes for prospective applications of our approach; our transition probabilities are not readily transferrable to other domains.

2	151	62	55	26	46
3	148	60	52	23	45
4	153	72	63	28	54
5	151	67	55	28	50
6	144	62	51	25	46
7	149	74	65	28	55
8	148	72	57	30	55
9	144	67	51	27	50
Min	144	60	51	23	45
Max	156	74	65	30	55

Briefly commenting on these results we note that there is relative stability in the measured results if probabilities are allowed to fluctuate within a reasonable range.

For some more insight as to what such fluctuations would mean, we remind the reader that HOU groups students according to their residence. If a group is less than ten students, then that group is dissolved and included in another group, maybe in another city. There is also the option that a group in a city grows too large and then has to be split. However, given the fact that to-date the geographical distribution of HOU student groups very much resembles the population distribution of Greece, a difference of ten students in a relatively small student population (for that particular programme) should make a difference of no more than one student group per module. Of course, it may well be that such a small difference (if it is an increase) might be simply absorbed into the current setting (for example, by increasing the number of students per group and better utilising existing classrooms but leaving the number of tutors intact).

5.2 Simulation with Markov Chains

In the integrated environment, we experimented with quite a few more options since it is relatively easier to specify a variable number of students admitted per year, as well as the specification of a range of probabilities to be used for the experiments.

We first experimented with the nine configurations set out earlier in this paper. The result was that the 20-year projections were quite close to each other (as happens in the results presented in Table 3), but it was interesting to see that the each 20-year experiment stabilised relatively early in the simulation.

There is a simple reason for that. We remind the reader that the most notable differentiation is that now each student is not atomically simulated throughout the study path but that students' population at each state are multiplied by the corresponding transition probabilities and that numbers are added up at resulting states, with no rounding involved. As a result this simulation is substantially faster than the discrete simulation but is also subject to relatively less variability in the results.

Following that initial experimentation round, we tried we several other configurations (Mitsionis, 2008), some of which involved the gradual increase of the number of students being admitted per year, as well as a relative fluctuation in several of the transition probabilities, well beyond the original nine configurations. The results showed, again, a fast stabilisation of the numbers of students in all modules.

A brief example will be now shown. We have experimented with a 20-year horizon, starting with a student intake of 100 and gradually increasing that intake to 200, over 5 years (adding 20 students per year). The majority of students (75%) register for both introductory modules and the rest (25%) register just for module 50, with the relative ratios remaining constant over the period that the student intake increases. When intake stabilizes at 200 annually, the ratios change to 50% each.

In that scenario, the transition probabilities from states (left column) to states (top row) are shown in Table 4.

Table 4. Model transition probabilities

	PP OUT		51	51	51 60	_51 61	51_60	51_61	51_62	51_60 61	51_60 62	51_61 62	51 60_61	51 60_62	51 61_60	51 61_62	51 62_60	51 62_61	TO_THESIS
	DROP	*50	*50	50_	50_	50_	20	20	20	20	20	20	20	20	20	20	20	20	<u>1</u>
*50	35%	13%	13%	13%	13%	13%													
*50 51	35%		7%	7%	7%	7%	7%	7%	7%	7%	7%								
50_51	10%			10%	10%	10%	10%	10%	10%	10%	10%	10%							
50_51 60					10%	10%	10%	10%	10%	10%	10%	10%	10%	10%					
50_51 61						11%	11%	11%	11%	11%	11%	11%			11%	11%			
50 51_60						11%	11%	11%	11%	11%	11%	11%	11%	11%					
50 51_61							13%	13%	13%	13%	13%	13%			13%	13%			
50 51_62							13%	13%	13%	13%	13%	13%					13%	13%	
50 51_60 61													10%	10%	10%	10%			60%
50 51_60 62													10%	10%			10%	10%	60%
50 51_61 62															10%	10%	10%	10%	60%
50 51 60_61													10%	10%					80%
50 51 60_62													10%	10%					80%
50 51 61_60															10%	10%			80%
50 51 61_62															10%	10%			80%
50 51 62_60																	10%	10%	80%
50 51 62_61																	10%	10%	80%

The student intake assumptions are shown in Table 5. We stress again that these are initial numbers for new students, at the start of each year. The actual values for these modules increase by the number of students who fail these particular modules the previous year and have to re-register. Following that, the results for a 20-year long simulation are shown in Table 6.

Table 5. Student intake assumptions

Year	Module 50	Modules 50, 51
1	25	75

30	90
35	105
40	120
45	135
50	150
100	100
	35 40 45 50

Table 6. Estimated student populations per module (Markov calculation)

Year	50	51	60	61	62
1	100	75	0	0	0
2	112	110	25	19	11
3	133	135	47	43	31
4	156	159	66	61	47
5	179	184	82	77	60
6	201	209	98	92	72
7	224	234	113	107	84
8	227	193	128	121	95
9	237	208	129	127	98
10	238	214	134	132	101
11	239	216	139	136	105
12	239	217	141	139	107
13	239	217	143	140	108
14	239	217	143	141	109
15	239	217	143	141	109
16	239	217	144	141	109
17	239	217	144	141	109
18	239	217	144	141	109
19	239	217	144	141	109
20	239	217	144	141	109

We have indicated the 8th year of the simulation as of particular interest because it is the first year which actually witnesses a stabilisation in the intake of new students. It is easy to see that all modules take one or two years more to stabilise while module 51 needs some time to take in the dramatic reduction of students witnessed in the 7th year, as a result of the shift in how students select modules. In the long run, one is interested in seeing that, eventually, modules 60 and 61 are equally favoured, even if 60 has first priority; this is because of the slight preference of 61 over 62. Students may take longer to arrive at 61 (as opposed to arriving at 60), but in a steady state they will probably select 61 over 62 and thus the overall numbers for 60 and 61 will add up to being about equal.

We are as of yet unsure as to whether the abundance of zeros in the transition probabilities matrix plays a (marginal or significant) role in speeding up stabilisation and it may be sensible to approach this problem by allowing each zero cell to have a small non-zero probability (and decreasing the initial non-zero probabilities by an equal small amount). However, even that approach has to been examined from the perspective of which goal we are trying to achieve. We refer the reader to Section 6 for the related discussion but we promptly point out that accuracy is hardly the first milestone in our endeavour.

6 On the Validity of the Prototyping Approach

We have focused our design and implementation on developing a proof of concept for providing us with initial coarse estimates for our postgraduate programme.

The estimates detailed above cannot yet be used anywhere near as a basis for decision making and there are two very significant reasons for this. First, the annual intake for the particular postgraduate programme has already increased from 120 students to 150 students, so the population hypothesis has changed. That increase has not yet been felt across all modules but, mainly in the junior ones. Second, while a certain organizational memory is being instilled in the junior modules, due to the fact that they are more heavily populated, that cannot be yet said for the senior year modules, which have mostly functioned with 2-3 small groups at most. But a small tutor population can have an amplified effect on the attitudes of students who, after finishing junior modules, gauge carefully which modules to select next. When there is not much experience to base that decision upon, numbers can fluctuate significantly. For example, that was the case with modules 61 and 62 of our programme, where attendance at module 62 stayed the same for a second year while attendance at module 61 nearly trebled. Since the fastest a student can expect to proceed to a thesis is two years and we are now just in the third year of the programme, we believe that year 2010 will be the first year where a steady-state as far as student enrolments and tuition paths can be expected. That year would most probably be the starting point for calculating more up-to-date and credible transition probabilities.

However, before we get there and as we aspire to eventually build a system for organization wide adoption, we have identified some major issues for our agenda.

First, we might reframe the requirements specification in another notation. The relatively recent adoption of belief networks as a tool for simulation modeling (Van Tol and AbouRizk, 2006) has also grasped our attention for modeling the alternative paths to graduation. A further reason for investigating other formalisms is that, for our proof of concept, we had to analyze individual student records to calculate the transition probabilities and, certainly, being able to derive them in a more cost-effective fashion is very appealing. Attempting to merge individual records towards more generic models has been also studied by Mathias *et al.* (2006) in the context of studying alternative counseling courses in the context of social welfare practicing.

We note that that our approach is also related more to the conventional AI planning approach as opposed to the Operations Research approach (Boutilier, 1999), since we do not associate rewards with any intermediate actions and since we treat students equally in terms of goal states, regardless of

how long they take to graduate. Factoring in rewards would make the model more complex and would, also, raise the issue of what would constitute a legitimate reward (it may not be easy to define, let alone calculate, whether it is better to have students oversubscribing into courses early in the program, thus raising the amount of resources required, or to have them distributed over years). Even a subtle reference to rewards makes it necessary to treat optimization aspects of the plan (as, is the case, for example, in Oddoye *et al.* (2007), who follow an Extend-like approach to estimate the impact of resources in the readiness of medical assessment units).

Still, our problem does not lie at the core of planning in the AI sense (Hendler *et al.*, 1990), since we are nor interested (yet) in computing optimal plans to a goal. Any sense of optimality, we believe, would take us back into the realm of the conventional OR approach and into Markov decision processes, since we would need to somehow associate each studying route with some measure of quality. Candidate measures could be either person-oriented (for example, a multi-objective criterion of minimizing the number of study years and the expenses due to travel), or system-oriented (for example, using the DEA (Charnes *et al.*, 1978) approach to calculate some measure of system efficiency; incidentally we note that there is no inherent limitation that does not allow our proposed approach to be taken up by conventional universities). Again, we need to keep in mind that applied problems which aspire to transcend the nature of basic scientific investigation towards fielding also need a certain amount of real-world-injected simplification, to manage complexity and to alleviate misunderstandings with model users.

The second issue has to do with the credibility of the transition probabilities. Each academic year sports a different configuration of the student population, with new students arriving each year. A certain organizational memory develops gradually based on students' perceptions about which modules are best to select given one's time available for studying or which modules are easier to follow based on one's earlier enrolments. This memory is subject to change every year and the associated transition probabilities inevitably change. One may use the statistics of all previous years (implementing a time window), possibly discounting for distant years. Another reasonable option is to just use the statistics for the previous year. Whichever decision one makes, the question that looms is whether this is a decision that must be made at the programme or at the university level or, even more importantly, whether this is a decision that statistically speaking matters. It is fortunate that this second issue can be most probably independently studied from the previous one using a theoretical or applied statistics toolkit and simulation.

The third issue has to do with the structural stability of any given degree programme and is the one with by far the most challenging consequences. As years go by, academic programmes change. When new modules are introduced or some modules are no longer offered, things are easy to model, because either the transition probabilities are calculated afresh or some transitions are trimmed. When, however, academic committees decide (and they rather often do) to move some modules up or down the academic requirements ladder (also affecting the precedence constraints), then modelling problems may occur. While it is straightforward to deal with such issues in an administrative context, and still easy to generate the state space model, deciding how one might make use of previously calculated transition probabilities for the new configuration seems to be a task that is not well defined.

We have not yet investigated the options for dealing with this problem. At present, we believe that the best outcome would be if theoretical analysis and statistical simulation might offer us some insight as regards the range of such changes, up to which we might be able to use default values without having to worry about the inevitable errors that incur due to the (educational) system's acquired momentum.

We note that the resolution of the latter two issues may transcend the prototype nature of our current implementation and may require the adoption of specific model description languages or process algebras that facilitate reasoning about simulation and about model consistencies (Pooley, 2007), or the adoption of models that explicitly allow for fuzziness in the specification of probabilities (Gien and Jacqmart, 2005).

Incidentally, the latter two issues also raise the question of the relative importance of the individual model parameters towards the credibility of the final results. To address this question, one has to bear in mind the eventual use of the simulation, when used as a decision making tool at a university level. Even if our results turn out to be very accurate, which we cannot now tell, we believe that we must resist the temptation to advise the university administration in terms of "so many groups will be formed in that module". Instead, we should be trying to advance more high-level predictions, such as "so many groups may be formed overall for this programme", even if our simulation is able to produce results on a module basis. Such a prediction may not be head-on but could still buy the university administration valuable planning time in estimating the amount of work and resources required for contract preparation, venue space procurement and related issues. It will probably be only after a series of successful high-level predictions that managerial confidence on the simulation tool will raise to a level that will allow the formation and testing of hypotheses at a higher resolution.

This observation partly takes us back to the point where individual technical steps might prove to be less important than initially expected. It is quite likely that their most important contribution may be to raise the organizational confidence that simulation is not just number crunching but that, instead, significant analysis and planning is involved when we use constraints to capture a system description. Acknowledging that user acceptance is a key success ingredient of such decision support systems, we have also identified as a future goal to attempt to replicate our experiments for programmes that have a much larger history at HOU and see how our methodology measures up with their actual enrolment figures. Going back to Chang and Radi's nomenclature (2001), we note that, currently at HOU, we attempt to simulate for medium-term planning in order to gain institutional acceptance and appreciation of the potential for policy formation planning.

The steps for any replication experiment are easy to identify. Initially, one should analyze the module precedence constraints that can be objectively derived from university regulations for a particular programme (see Section 3.3). With those at hand one should then *automatically* generate the state space graph (see Section 3.1). In any case the precedence constraints can help one check more readily the correctness of the state space graph. Finally, one should then calculate the state transition probabilities (see Section 3.2). Where many years are involved, one may choose to either pick the latest numbers or use averages for a time window (perhaps, also discounting more distant years along the way). The above can be now all embedded as steps in the simulation environment (preferably as shown in Section 4.2) and therein starts the actual experimentation.

7 Conclusions and future directions

Modelling the size of a student population and how such a population is spread into modules of a programme with arbitrary precedence requirements among its modules can surely aid a programme's management to plan proactively. In this paper we have shown the key technical ingredients of a system that can provide estimates and we have also presented which aspects of such a system need further research, either in terms of system integration or in terms of robust modelling in circumstances of change.

We acknowledge that population modelling and estimation may be at a wide tangent to policies as practiced by today's universities. We also acknowledge that (even) the strategy consensus required for fielding such systems to actually support university administration may take indefinitely longer than the resolution of the technical and scientific issues that we have already identified. Actually, such consensus is probably of a political rather than a technological nature (Ringwood *et al.*, 2003).

None of the techniques and tools we have used aspires to further the state of the art in each of the respective fields. Still, putting these techniques together and being able to develop models that decision-making users can understand gives rise to the emergence of new modelling tools and methodologies, like the one we have proposed in this paper. This will equip educational managers with the insight they direly need in order to contemplate policy alternatives and to reflect upon past decision based on actual data (Scott, 2005), which takes the pressure away from using such tools as part of everyday fine-tuning administration. So, even if results never reach the level of statistical significance, it will always be up to innovative managers to use simulation as a tool for exploring what-if scenarios to generate reflections about future policy directions.

Acknowledgements

Michalis Xenos (HOU) first implemented a short program to help steer junior undergraduate Informatics students at HOU through the course selection requirements and priorities.

Nicos Karacapilidis (University of Patras) offered insight into the options available by industrial class simulation software and initiated a liaison between some of the authors.

We acknowledge the help provided by reviewers and editors during earlier submissions; these have resulted in a much improved presentation, particularly with respect to bringing out more clearly the milestones of this on-going project.

Code and data are all available for academic purposes. The software and default projects can be downloaded at http://users.thesp.sch.gr/vmitsionis/sn_predictor/ (also available in English).

References

Boutilier, C., Dean, T., and Hanks, S. (1999). Decision-Theoretic Planning: Structural Assumptions and Computational Leverage. *Journal of Artificial Intelligence Research* 11: 1-94.

Chang, G.-C., and M. Radi (2001). Educational planning through computer simulation. Paris, UNESCO.

Charnes, A., W.W. Cooper and E. Rhodes (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research* 2: 429-444.

Gien, D., and S. Jacqmart (2005). Design and simulation of manufacturing systems facing imperfectly defined information. *Simulation Modelling Practice and Theory* 13: 465-485.

Grinstead, C.M., and J.L. Snell (1997). *Introduction to probability*. American Mathematical Society, 2nd revised edition.

Hadzilacos, Th., D. Kalles, C. Pierrakeas, and M. Xenos (2006). On Small Data Sets revealing Big Differences. *Panhellenic Conference on Artificial Intelligence*, Heraklion, Greece.

Hendler, J., A. Tate, and M. Drummond (1990). Al Planning: Systems and Techniques. *Al Magazine* 11(2): 61-77.

Iman, R.L., J.C. Helton, and J.E. Campbell (1981). An approach to sensitivity analysis of computer models, Part 1. Introduction, input variable selection and preliminary variable assessment. *Journal of Quality Technology* 13(3): 174-183.

Kalles, D., and C. Pierrakeas (2006a). Analyzing Student Performance in Distance Learning with Genetic Algorithms and Decision Trees. *Applied Artificial Intelligence* 20(8): 655-674.

Kalles, D., and C. Pierrakeas (2006b). Using Genetic Algorithms and Decision Trees for a posteriori Analysis and Evaluation of Tutoring Practices based on Student Failure Models. 3^{rd} IFIP Conference on Artificial Intelligence Applications and Innovations, Athens, Greece.

Kalles, D., C. Pierrakeas, and M. Xenos (2008). Intelligently Raising Academic Performance Alerts. 1st International Workshop on Combinations of Intelligent Methods and Applications, a workshop of the 18th European Conference on Artificial Intelligence, pp. 37-42, Patras, Greece.

Mathias, K.K., Isenhour, C., Dekhtyar, A., Goldsmith, J., and Goldstein, B. (2006). *Eliciting and Combining Influence Diagrams: Tying Many Bowties Together*. University of Kentucky, Department of Computer Science, Technical Report TR453-06.

Mitsionis, V. (2008). *Information System for estimating the development of students population*. M.Sc. Dissertation (in Greek), Hellenic Open University Patras, Greece.

Oddoye, J.P., D.F. Jones, M. Tamiz, and P. Schmidt (2007). Combining simulation and goal programming for healthcare planning in a medical assessment unit. *European Journal of Operational Research* 193: 250-261.

Open Learning (2004), Special issue 19(1) on "Student retention in open and distance learning".

Pooley, R. (2007). Behavioural equivalence is simulation modelling. *Simulation Modelling Practice and Theory* 15: 1-20.

Ringwood, J.V., F. Devitt, S. Doherty, R. Farell, B. Lawlor, S.C. McLoone, S.F. McLoone, A. Rogers, R. Villing, and T. Ward (2005). A resource management tool for implementing strategic direction in an academic department. *Journal of Higher Education Policy and Management* 27(2): 273-283.

Scott, D. (2005). Retention, completion and progression in tertiary education in New Zealand. *Journal of Higher Education Policy and Management* 27(1): 3-17.

Van Tol, A.A., and S.M. AbouRizk (2006). Simulation modelling decision support through belief networks. *Simulation Modelling Practice and Theory* 14: 614-640.

Webster, T. (1997). Cost analysis and its use in simulation of policy options: the Papua New Guinea education finance model. *International Review of Education* 43(1): 5-23.

Xenos, M., Ch. Pierrakeas, and P. Pintelas (2002). A survey on student dropout rates and dropout causes concerning the students in the Course of Informatics of the Hellenic Open University. *Computers and Education* 39: 361-377.