Fuzzy Multiple Ordering Criteria for Examination Timetabling

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Abstract. Ordering exams by simultaneously considering two ordering criteria using a fuzzy expert system is presented in this paper. Combinations of two of the three ordering criteria *largest degree*, *saturation degree* and *largest enrollment* are considered. The fuzzy weight of an exam is used to represent how difficult it is to schedule. The decreasingly ordered exams are sequentially chosen to be assigned to the last slot with least penalty cost value while the feasibility of the timetable is maintained throughout the process. Unscheduling and rescheduling exams is performed until all exams are scheduled. The proposed algorithm has been tested on 12 benchmark examination timetabling datasets and the results show that this approach can produce good quality solutions. Moreover, there is significant potential to extend the approach by including a larger range of criteria.

1 Introduction

Examination timetabling is a problem of allocating a timeslot for all exams in the problem instances within a limited number of permitted timeslots, in such a way that none of the specified hard constraints are violated. In addition to the hard constraints, there are often many soft constraints which are desirable (but not essential) to satisfy. In most cases, the problem is highly constrained and, moreover, the set of constraints which are required to be satisfied is different from one institution to another as reported by Burke et al. [6]. In general, the most common hard constraint is to avoid any student being scheduled for two different exams at the same time.

In practice, each institution usually has a different way of evaluating the quality of the developed timetable. In many cases, the quality is calculated based on a penalty function which represents the degree to which the constraints are satisfied.

Over the years, numerous approaches have been investigated and developed for exam timetabling. Such approaches include constraint programming, graph colouring, and various metaheuristic approaches including genetic algorithms, tabu search, simulated annealing, the great deluge algorithm, and hybridized methods which draw on two or more of these techniques. Some recent important papers which reflect this broad range of activity are [7, 9, 14, 16, 18, 22, 23, 28, 35]. Discussions about other approaches can be found in papers by Bardadym [3], Burke et al. [11], Burke and Petrovic [13], Carter [15], Carter and Laporte [17], De Werra [21], Petrovic and Burke [29], and Schaerf [33].

Approaches which order the exams prior to assignment to a timeslot have been discussed by several authors including Boizulmault et al. [4], Brailsford et al. [5], Burke et al. [10], Burke and Newall [12], Burke and Petrovic [13] and Carter et al. [16]. Carter et al. [16] report the use of four ordering criteria to rank the exams in decreasing order to estimate how difficult it is to schedule each of the exams. They considered largest degree, saturation degree, largest weighted degree and largest enrollment as their ordering criteria. These criteria were used individually each time they wanted to order the exams by the selected ordering criteria. Then, the exams were selected sequentially and assigned to a slot that satisfied all specified constraints. If no clash free slot was found, backtracking was implemented. The process was continued until all the exams were scheduled and a feasible solution was produced.

Since being introduced by Zadeh in 1965 [36], fuzzy methodologies have been successfully applied in a wide range of real world applications. Examples from scheduling, planning and timetabling problem domains include fuzzy evaluation functions utilized in generator maintenance scheduling by Dahal, Aldridge and McDonald [20], and Abboud et al. [1] who used fuzzy target gross sales (fuzzy goals) to find 'optimal' solutions of a manpower allocation problem, where several company goals and salesmen constraints need to be considered simultaneously. Fuzzy methodologies have been investigated for other timetabling problems such as aircrew rostering [34], driver scheduling [26] and nurse rostering [24]. Furthermore, fuzzy techniques can represent and deal with multi-criteria decision making described by Raj and Kumar [31], and Lee and Kuo [25]. However, as far as we are aware, fuzzy methods have not yet been implemented in the context of examination timetabling.

In this paper, a fuzzy expert system is used to rank exams based on an assessment of how difficult it is to schedule the exams taking into account multiple criteria. By considering more than one criteria to rank the exams, it is hoped that rankings are produced that better reflect the actual difficulty of placing the exam, as several factors are simultaneously taken into account. The fuzzy multiple criteria ordering method employed here differs from other multicriteria approaches to examination timetabling, such as described in Arani and Lotfi [2], Burke et al.[8], Lotfi and Cerveny [27], and Petrovic and Bykov [30]. In our approach, two ordering criteria are simultaneously considered to rank the exams, whereas in [2, 8, 27, 30] they used each criterion to measure the violation of a corresponding constraint.

In the following section, the proposed algorithm is explained in detail. Section 3 describes the experiments carried out and the results obtained. Discussion and conclusions are presented in Sections 4 and 5 respectively.

2 Methods

In real world decision making, many decisions are required to take into account several factors simultaneously under various sets of constraints. Usually it is not known which factor(s) need to be emphasized more in order to generate a better decision. Somehow a trade off between the various (potentially conflicting) factors must be made. The general framework of fuzzy reasoning allows the handling of much of this uncertainty. Fuzzy systems usually employ fuzzy sets, which represent uncertainty by numbers in the range [0, 1]. These numbers represent the degree of membership with which the corresponding elements belong to the set. The precise meaning of membership degrees is not rigidly defined, but is supposed to capture the 'compatibility' of an element to the notion of the set.

Fuzzy expert systems are used for representing and inferring with knowledge that is imprecise, uncertain, or unreliable. They consist of four main interconnected components: an input fuzzifier, a set of rules, an inference engine, and an output processor (defuzzifier). Rules which connect input variables to output variables in 'if … then …' form are used to describe the desired system response in terms of *linguistic* variables (words) rather than mathematical formulae. The number of rules depends on the number of inputs, outputs, and the system's behavior goals. Once the rules have been established, a fuzzy expert system can be viewed as a non-linear mapping from inputs to outputs. A full description of the functioning of fuzzy expert systems is not given here for reasons of space, but the interested reader is referred to Cox [19] for a simple treatment or Zimmerman [37] for a more complete treatment.

A number of experiments were carried out in which progressively more sophisticated fuzzy expert systems were created to sort exams prior to a construction technique was applied as shown in the general framework in Fig. 1. Initially single criterion ordering was implemented to verify the correct functioning of the construction algorithm. Next, a fixed fuzzy model that took into account multiple criteria was implemented. Following this, a straight-forward tuning procedure was implemented to investigate whether the initial choice of fuzzy model was appropriate and this tuning procedure was applied to different combinations of multiple ordering criteria. The following ordering criteria were considered when selecting which exam should be scheduled first:

i. Number of conflict exams, *largest degree* (LD)
ii. Number of student enrolled, *largest enrollment* (LE)
iii. Number of available slot, *saturation degree* (SD)

In each case, two out of the three criteria above were selected as input variables. Each of the input variables were assigned three linguistic terms; fuzzy sets corresponding to meanings of *small*, *medium* and *high*, referred to as 'membership functions'. Initially, these were chosen arbitrarily to span the universe of discourse of the variable (the range over which the variable spans). A rule set connecting these input variables to a single output variable, *exam_weight*, was constructed. Standard Mamdani style fuzzy inference was implemented with standard Zadeh (min-max) operators (see [19] or [37] for explanations of the standard Mamdani style fuzzy inference). Centroid defuzzification was then utilized to obtain a single crisp (real) value for *exam_weight*. Further detail on the terms and rules used in each case are given in Section 3.

```
Sort unscheduled exams using selected multiple ordering criteria;
Insert exams into the last timeslot with least penalty;
While there exist unscheduled exam
   Perform the process for scheduling the unscheduled exams;
   Sort unscheduled exams using selected multiple ordering criteria;
End while
```

Fig. 1. Pseudo code for general framework of sequential construction heuristic

The sequential construction heuristic described by Carter et al. [16], but with a modification in the backtracking process, was applied to construct a timetable once the exams had been ordered by the fuzzy expert system. The algorithm used is detailed in Fig. 2.

The developed algorithm required the following steps to assign all exams to a timeslot. First, the exams were ordered by some criteria in descending order. Then, exams were selected sequentially and assigned to the last available timeslot in the list with minimum penalty cost. If no clash free timeslot was available, the exam was skipped and the process continued with the next exam. The skipped exams were then revisited and a process for scheduling the unscheduled exam was performed (see Fig.2). This technique is different from the one Carter used because minimum disruption cost was not used to select a timeslot for reshuffling the scheduled exams if there was a tie between several timeslots. Instead, the timeslot was selected randomly from the list of timeslots with the same minimum number of scheduled exams that needed to be ‘bumped back’.

```
k := number of unscheduled exams;
For u := 1 to k
   Select exam[u];
   Find timeslots where exam[u] can be inserted with minimum number
   of scheduled exams need to be removed from the timeslot;
   If found more than one slot with the same number of scheduled ex-
   ams need to be removed
     Select a timeslot randomly from the candidate list of slots, ts;
   End if
   c := number of exam in timeslot ts_u that conflict with exam[u];
   For m := 1 to c
       Select exam[m];
      If found another timeslot with minimum cost to move exam[m]
        Move exam[m] to the timeslot;
      else
        Bump back exam[m] to unscheduled exam list;
      End if
   End for
   Insert exam[u] to timeslot ts_u;
   Remove exam[u] from unscheduled exam list;
End for
```

Fig. 2. Pseudo code for scheduling the unscheduled exams

A proximity cost function was used to measure the timetable quality. The maximum capacity for each timeslot was not taken into account. Only feasible timetables were accepted and the penalty function was utilized to try to spread out each student’s schedule. If two exams scheduled for a particular student are *t* timeslots apart, the weight is set to $w_t = 2^{5-t}$ where $t \in \{1,2,3,4,5\}$. The weight is multiplied by the number of students that sit for both of the scheduled exams. The average penalty per student is calculated by dividing the total penalty by total number of students. The following formulation was used (adopted from Burke et al. [9]):

$$\text{minimize} \quad \frac{\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} s_{ij}\, w_{(p_j - p_i)}}{T} \tag{1}$$

where N is number of exams

s_{ij} is number of student enrolled both exam i and j

p_i is the timeslot where exam i is scheduled

p_j is the timeslot where exam j is scheduled

T is total number of student

and subject to $1 \leq p_j - p_i \leq 5$

Table 1. Characteristics of the problem

No. of Student	No. of Exams	No. of Student	No. of Slots
CAR-F-92	543	18419	32
CAR-S-91	682	16925	35
EAR-F-83	190	1125	24
HEC-S-92	81	2823	18
KFU-S-93	461	5349	20
LSE-F-91	381	2726	18
RYE-F-92	486	11483	23
STA-F-83	139	611	13
TRE-S-92	261	4360	23
UTA-S-92	622	21266	35
UTE-S-92	184	2750	10
YOR-F-83	181	941	21

The algorithm was developed using java based object oriented programming. The fuzzy inference engine developed by Sazonov et al. [32] was implemented. The experiments were run on a PC with a 1.8 GHz Pentium 4 and 256MB of RAM. Carter's publicly available exam timetabling datasets were used in the experiments. Table 1 reproduces the problem characteristics.

3 Experimental Results

In this section the various experiments that were carried and the results obtained in each case are presented.

3.1 Experiment 1

In order to test our minor modification to the sequential construction method previously developed by Carter et al. [16], the algorithm was initially run without implementing fuzzy ordering. That is, in this experiment, the exams in the problem instances were ordered based on a single ordering criterion. All the exams were then selected to be scheduled in sequence based on this ordering.

The results are shown in columns 2, 3 and 4 of Table 2. It can be seen that, as expected, when compared to Carter's results (column 5 of Table 3) the algorithm produced broadly similar results: a slightly better timetable was obtained for the CAR-F-92 and CAR-S-91 dataset; the other datasets were comparable.

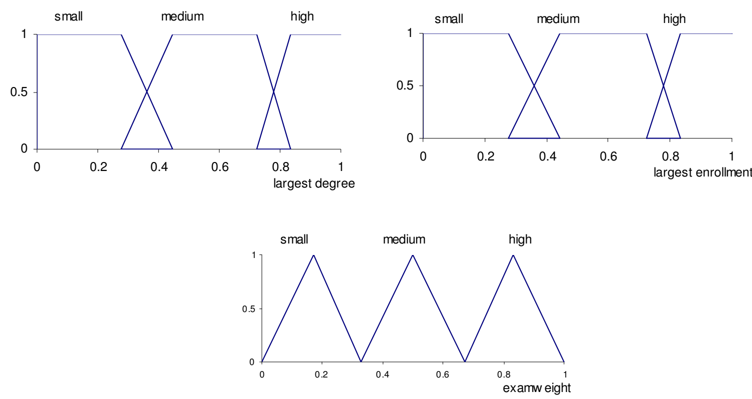
Table 2. Experimental results for the different ordering criteria that were implemented

	Experiment 1			Experiment 2	Experiment 3	Experiment 4
Dataset	LD	SD	LE	LD + LE (fixed FES)	LD + LE (tuned FES)	SD + LE (tuned FES)
CAR-F-92	5.56	5.50	5.03	5.65	4.60	**4.56**
CAR-S-91	6.38	5.91	5.90	6.31	5.60	**5.29**
EAR-F-83	40.58	49.10	45.88	48.14	38.41	**37.02**
HEC-S-92	14.98	14.27	14.94	16.93	12.53	**11.78**
KFU-S-93	18.63	18.60	16.46	18.29	16.53	**15.81**
LSE-F-91	15.08	13.46	14.52	16.84	12.35	**12.09**
RYE-F-92	13.33	15.32	11.97	11.80	11.03	**10.35**
STA-F-83	173.09	178.24	171.87	161.21	**160.42**	160.75
TRE-S-92	10.98	10.81	9.93	10.36	9.05	**8.67**
UTA-S-92	4.48	3.83	4.78	5.16	3.87	**3.57**
UTE-S-92	35.19	33.14	28.80	30.54	28.65	**27.78**
YOR-F-83	45.60	45.27	43.53	46.41	41.37	**40.66**

3.2 Experiment 2

In this experiment, the unscheduled exams are ordered using *largest degree* and *largest enrollment* by applying fuzzy reasoning as described earlier. The membership functions and rules used in this experiment are shown in Figure 3. The choice of these membership functions was based on 'trial and error' to test how the algorithm would work when exams were ordered with the aid of fuzzy reasoning. The results are shown in column 5 of Table 2.

This experiment demonstrated that by evaluating two ordering criteria simultaneously better timetables can be produced. For CAR-S-91, TRE-S-92 and YOR-F-83 this multiple ordering criteria technique produced better results than the single *largest degree* ordering criteria in Experiment 1. It also produced better results compared to the single *saturation degree* ordering criteria in STA-F-83, UTE-S-92 and YOR-F-83 datasets.



Fuzzy Rules :

if largest degree is high and largest enrollment is high then examweight is very high
if largest degree is high and largest enrollment is medium then examweight is medium
if largest degree is high and largest enrollment is small then examweight is small
if largest degree is medium and largest enrollment is high then examweight is high
if largest degree is medium and largest enrollment is not high then examweight is medium
if largest degree is small and largest enrollment is high then examweight is medium
if largest degree is small and largest enrollment is not high then examweight is very small

Fig. 3. Fuzzy model for Experiment 2.

3.3 Experiment 3

As an extension to Experiment 2, it was decided that a restricted form of exhaustive search would be used to find the most appropriate shape for the fuzzy terms in the fuzzy expert system. There are very many alternatives that may be used in constructing a fuzzy model. For the next two experiments we arbitrarily restricted the search based on the fuzzy membership functions as shown in Fig. 4. Triangular shape membership functions were employed to represent *small*, *medium* and *high*. However, the fuzzy model was then altered by moving the point *cp* along the universe of discourse. This point corresponded to the right edge for the term *small*, the centre point for the linguistic label *medium* and the left edge for the term *high*. A search was then carried out to find the best set of *cp* parameters (there was one for each linguistic variables – i.e. a *cp* parameter for each of the two input variables and the output variable).

During the search for the optimal fuzzy model, the center point for any of the fuzzy variables can take a value between 0.0 and 1.0 inclusively. We use 0.1 increments for datasets that have 400 and fewer exams and 0.25 increments are used for datasets that have more than 400 exams. In some circumstances, only two linguistics variables are applicable for any of the fuzzy variables. As shown in Fig. 5 (a), only the linguistic variables *medium* and *high* are used when the center point = 0.0. And in Fig. 5 (b), if the center point =1.0 only the *small* and *medium* linguistic variables are employed.

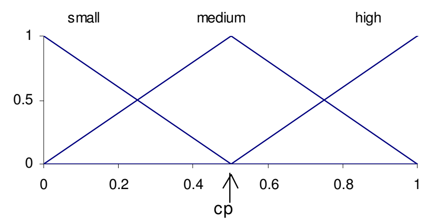
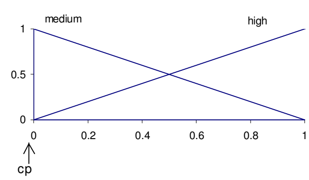
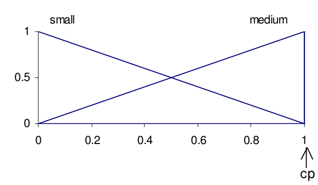


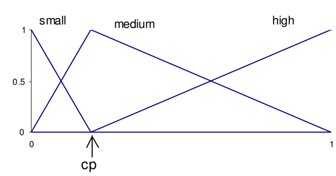
Fig. 4. Membership function for fuzzy linguistic variables



(a) cp =0.0



(b) cp = 1.0



(c) 0 < cp <1

Fig. 5. Range of possible membership function linguistic labels

In Experiment 3, *largest degree* and *largest enrollment* were used as the fuzzy input variables. The fuzzy rules used are as follows:

Fuzzy Rules:

if largest degree is high and largest enrollment is high then examweight is very high
if largest degree is high and largest enrollment is medium then examweight is high
if largest degree is high and largest enrollment is small then examweight is medium

if largest degree is medium and largest enrollment is high then examweight is high
if largest degree is medium and largest enrollment is medium then examweight is medium
if largest degree is medium and largest enrollment is small then examweight is small
if largest degree is small and largest enrollment is high then examweight is medium
if largest degree is small and largest enrollment is medium then examweight is small
if largest degree is small and largest enrollment is small then examweight is very small

The results from Experiment 3 are shown in column 6 of Table 2. It is obvious that this experiment produced better results compared with Experiment 2, for all of the datasets. In comparison with Experiment 1, all results are better except for the KFU-S-93 and UTA-S-92 datasets.

3.4 Experiment 4

In this experiment saturation degree and largest enrollment were used as the fuzzy input variables. Fuzzy rules were defined as follows:

Fuzzy Rules:
if largest enrollment is high and saturation degree is high then examweight is medium
if largest enrollment is high and saturation degree is medium then examweight is high
if largest enrollment is high and saturation degree is small then examweight is very high
if largest enrollment is medium and saturation degree is high then examweight is small
if largest enrollment is medium and saturation degree is medium
then examweight is medium
if largest enrollment is medium and saturation degree is small then examweight is high
if largest enrollment is small and saturation degree is high then examweight is very small
if largest enrollment is small and saturation degree is medium then examweight is small
if largest enrollment is small and saturation degree is small then examweight is medium

The results from this experiment are shown in column 7 of Table 2. Except for the STA-F-83 dataset, this experiment has generated better results compared to all the other experiments.

4 Discussion and Evaluation

From Table 2 it can be seen that the initial fuzzy model (Experiment 2) produced comparable results to the single criteria ordering (Experiment 1). This indicates that care must be taken when applying fuzzy techniques: it is certainly not the case that just because it is fuzzy it is necessarily better. In all cases, tuning the fuzzy model produces better results, as might be expected. This confirms our hypothesis that simultaneous ranking of multiple criteria can produce better results.

Table 3 shows the performance of our algorithm in comparison with selected recently published results on Carter's benchmarks. The best result amongst the compared techniques for each dataset is highlighted in bold font. Overall, the performance of our algorithm is comparable to the others. However, we are more interested in comparing our results to Carter's results [16], because as mentioned in Section 2, we adopted their sequential construction heuristic with some modification.

Basically, there are three differences between these two algorithms. Firstly, a search is carried out to find the clash free timeslot with least penalty cost in order to assign each exam to a timeslot. If several timeslots are available, then the last available timeslot in the list will be selected. Here, it was found that the choice of assigning exams to the last available timeslot or the first available timeslot did not make much difference, because the main objective was to spread out the student's timetable. 'Side constraints', such as whether an exam with many students should be scheduled earlier, were not considered. Regardless of this, our algorithm will produce a different timetable but with a penalty cost that is almost the same. Meanwhile, Carter chooses the first clash free timeslot found in which to assign the exam.

Secondly, we randomly select a timeslot for reshuffling an exam if several timeslots are available, whereas Carter used minimum disruption cost to break any ties. The effect of these two differences can be seen in the Experiment 1 results. In Experiment 1, a single criterion ordering is used but without fuzzy evaluation. By implementing these two changes, a better timetable for the CAR-F-92 and CAR-S-92 datasets was produced. The other datasets results are also comparable to Carter's.

Table 3. Results Comparison

Dataset	Best Fuzzy Multiple Ordering Criteria	Burke et al. [9]	Caramia et al. [14]	Carter et al. [16]	Casey and Thompson [18]	Merlot et al. [28]
CAR-F-92	4.56	**4.2**	6	6.2	4.4	4.3
CAR-S-91	5.29	**4.8**	6.6	7.1	5.4	5.1
EAR-F-83	37.02	35.4	**29.3**	36.4	34.8	35.1
HEC-S-92	11.78	10.8	**9.2**	10.8	10.8	10.6
KFU-S-93	15.81	13.7	13.8	14	14.1	**13.5**
LSE-F-91	12.09	10.4	**9.6**	10.5	14.7	11
RYE-F-92	10.35	8.9	**6.8**	7.3	**-**	8.4
STA-F-83	160.42	159.1	158.2	161.5	**134.9**	157.3
TRE-S-92	8.67	**8.3**	9.4	9.6	8.7	8.4
UTA-S-92	3.57	**3.4**	3.5	3.5	-	3.5
UTE-S-92	27.78	25.7	**24.4**	25.8	25.4	25.1
YOR-F-83	40.66	36.7	**36.2**	41.7	37.5	37.4

The third difference is that we have implemented fuzzy techniques to simultaneously evaluate multiple criteria to ranking the exams. As can be seen in Table 3, our algorithm produced a better timetable for CAR-F-92, CAR-S-91, STA-F-83, TRE-S-92 and YOR-F-83 datasets compared to Carter's results. The best fuzzy results shown in column 2 of Table 3 are generated when the best fuzzy model is identified during the tuning process. The best fuzzy model for each dataset is presented in Fig. 6 and Fig. 7. From these, it can be seen that the membership functions differ in each case – i.e. there is no generic fuzzy model which suits all the datasets.

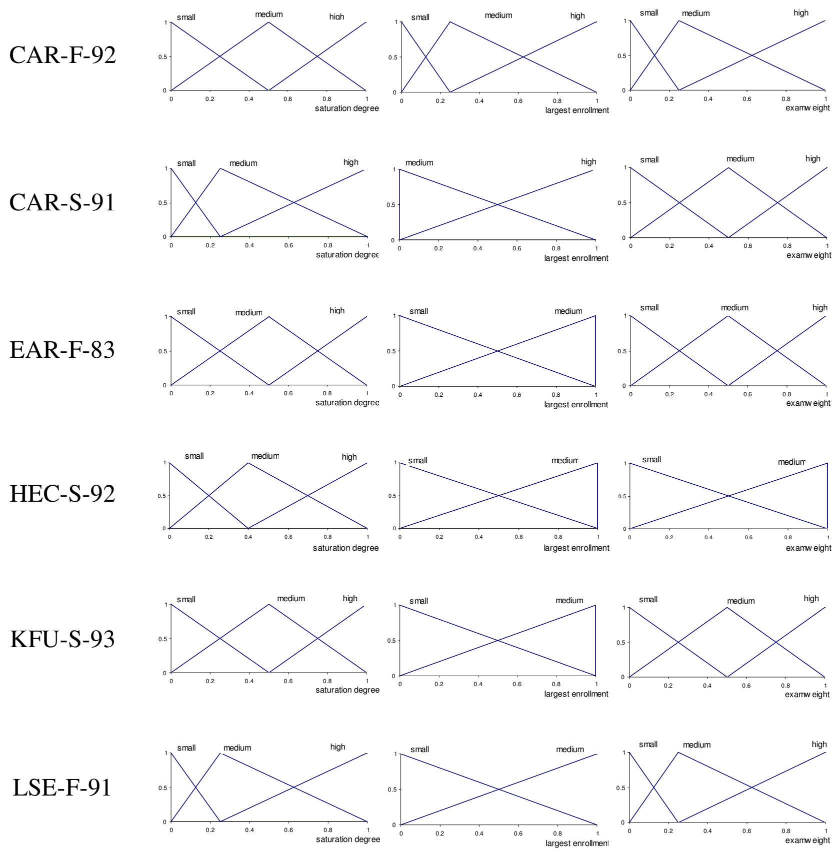


Fig. 6. Best fuzzy model for datasets CAR-F-92, CAR-S-91, EAR-F-83, HEC-S-92, KFU-S-93 and LSE-F-91

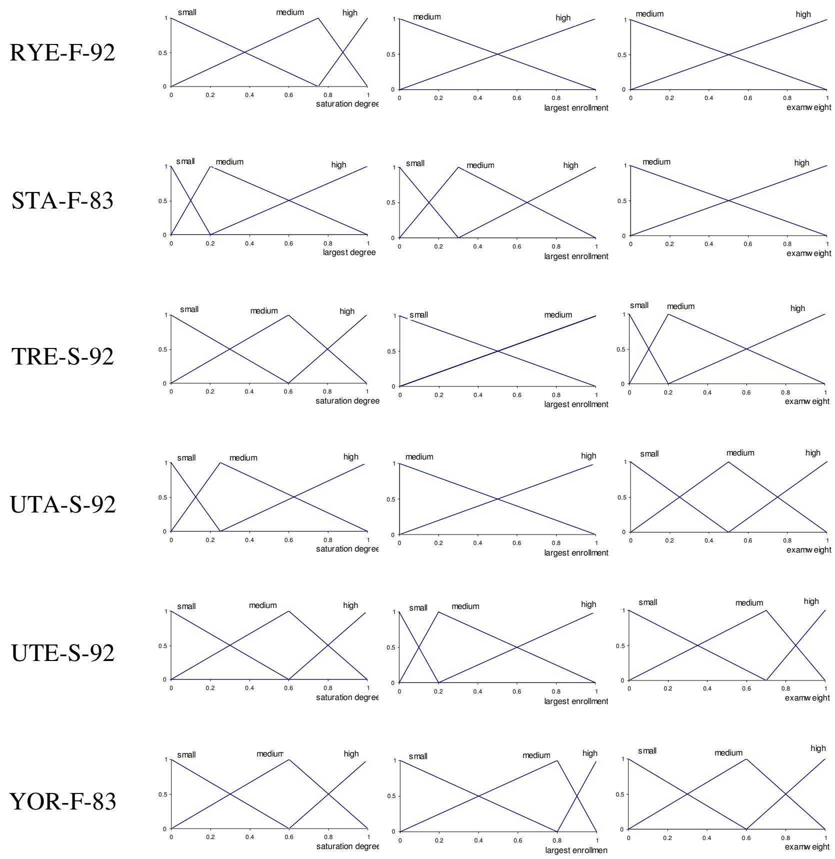


Fig. 7. Best fuzzy model for datasets RYE-F-92, STA-F-83, TRE-S-92, UTA-S-92, UTE-S-92 and YOR-F-83

5 Conclusions

As far as the authors are aware, no other published work has described the exploration of fuzzy methodologies for simultaneously ordering exams in the construction of examination timetables. In this study, we investigated a fuzzy expert system to use multiple ordering criteria simultaneously in an attempt to better represent the difficulty of scheduling exams. Our evaluation indicates that better solutions can be produced when exams are ordered by several criteria before the search process starts. This has confirmed our hypothesis that the exploration of different methodologies to achieve multi criteria orderings may be beneficial. The experiments carried out have demonstrated that the fuzzy tuning employed does improve the performance.

We are encouraged by these promising initial results and aim to extend this work further. Future research avenues may include:

- investigating other combinations of ordering criteria
- investigating different sets of fuzzy rules and fuzzy membership functions
- exploring the use of more sophisticated optimization algorithms when tuning these and other fuzzy models
- testing the algorithms on capacitated benchmark problems

Acknowledgements. This research work was supported by the Universiti Teknologi Malaysia (UTM) and the Ministry of Science, Technology and the Environment Malaysia (MOSTE).

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