# American Scientific Research Journal for Engineering, Technology, and Sciences (ASRJETS) <br> ISSN (Print) 2313-4410, ISSN (Online) 2313-4402 <br> © Global Society of Scientific Research and Researchers 

# Faculty Course Scheduling Optimization 

Demy F. Gabriel ${ }^{\mathrm{a}^{*}}$, Joey Maria A. Pangilinan ${ }^{\text {b }}$<br>${ }^{a, b}$ Saint Louis University, Baguio City, 2600, Philippines<br>${ }^{a}$ Email: demygabriel@yahoo.com<br>${ }^{b}$ Email: jmapangilinan@slu.edu.ph


#### Abstract

Faculty course scheduling optimization is the second of the three stages of the University Course Timetable Problem optimization. The optimization process was modeled using genetic algorithms, binary integer programming, and linear programming. There are four simple problems and four difficult problems that were used in the study. Linear programming had the highest total rating but infeasible because it produced fractional timetable values. Since the output of both genetic algorithms and binary integer programming were feasible and the total rating of binary integer programming was higher, it was considered as the best model. The binary integer programming model gives the optimal solution for as long as formulation of the needed functions and constraints is possible and the solver can process them. An alternative model is the genetic algorithms that is capable of giving feasible solutions even in very complicated scheduling conditions. The linear programming model is the basis of the correctness of the output provided by the other two models because its optimum value is usually higher than the other models.


Keywords: Course scheduling; optimization; linear programming; genetic algorithms; binary integer programming.

## 1. Introduction

Faculty course scheduling optimization is the process of selecting the most preferred schedules of the course subjects handled by faculty members in the university. This study is the second of the three stages of the University Course Timetable Problem (UCTP) optimization of the timetabling of the subjects of faculty members. The first stage of the UCTP optimization is the Faculty Course Assignment Optimization and the third part is the Faculty Room Assignment Optimization.

[^0]The scheduling process embraced the technique used by the Genetic Algorithms (GA), Binary Integer Programming (BIP), and Linear Programming (LP) models. The technique that produced the feasible and highest rating was considered as the best model.

The purpose of the faculty course scheduling optimization is to maximize the total rating given by the faculty members to the available schedules for the week. This research contributes to the field of course timetabling optimization. The hard and soft constraints applied to a local setting which is the concern of the study are actually different from the existing researches. The way of formulating the objective functions and constraints are also different. The paper tries to compare the results using the principles of integer programming, linear programming model and genetic algorithm. This study may help any future university course timetabling problem UCTP researches that might originate locally. An automated timetable eliminates the perennial headache for schools on creating course timetable that requires administrative personnel to spend value time at the task at the beginning of the school year or semester [1]. Since this study aims to provide an optimized course schedule, this solves the problem of too general automated timetables that are available in the market which usually do not fit the specific requirements of a local university. This study can be used by a local university helps facilitate and reduces the cost of the timetabling process usually done before the start of semester.

An automated timetabling similar to this one help reduces the amount of time needed to produce not only a feasible but also an optimized timetabling. This helps the usual problem of solving a real world timetabling problem manually which often requires a significant amount of time. It may take some time, several days or even weeks [2]. This study is one of the many researches that had been proposed in order to provide automated support for human timetables. There are several publications on university course timetabling models and methods but the number of papers describing actual implementations of automated timetabling systems appears to be rather limited. In many cases, numerical results are reported for data sets that are "inspired" by a realworld setting, but it remains unclear to which extent an automated timetabling system has actually been implemented [3].

This study will be used by the university to optimize the course timetabling problem. This includes all lecture and laboratory subjects. Faculty members will initially provide their ratings to all of the available schedules within the department. The system will schedule the subjects that were assigned to the faculty members such that the overall rating will be optimum but will not violating any requirement of the standard scheduling process. This should be done using three techniques which are linear programming, binary integer programming and genetic algorithm. The technique that can give the best and appropriate assignment model will be adopted by the department. The critical part of the study was the formulation of the problems to come up with the correct functions that would satisfy the requirement of the objectives and the constraints of both the BIP and LP models, and creation of the required program of the algorithm needed for the GA model.

## 2. Material and Methods

The previous BIP output of the faculty course assignment optimization were the raw data that are needed in the faculty course scheduling optimization because this model produced the feasible and highest ratings among the
three models. There are four simple problems and four difficult problems used in the study. The simple problems comprised of 10 subjects with 4 faculty members and 3 block sections while the four difficult problems had 90 subjects with 10 faculty members and 12 blocks. Both simple and difficult problems had lectures and laboratory classes with the lecture classes having the variable duration of one hour to five hours.

Faculty members will initially provide their ratings to all of the available schedules within the department. The system will schedule the subjects that were assigned to the faculty members such that the overall rating will be optimum but will not violating any requirement of the standard scheduling process. This should be done using three techniques which are linear programming, binary integer programming and genetic algorithm. The technique that can give the best and appropriate assignment model will be adopted by the department.

Four simple and four difficult assignments were used in the scheduling process. The simple problems were labeled $1,2,3$, and 4 while the difficult problems were $5,6,7$, and 8 . Only simple problem no 2 was illustrated and discussed fully. The remaining simple problems and difficult problems were only included in the summary. The population used in the faculty course scheduling were the optimized data taken in the faculty course assignment optimization. A sample of this is the simple problem no. 2 given in the table 1 below.

Table 1: Simple problem no. 2

| subj | fac | hr | type | blk |
| :---: | :---: | :---: | :---: | :---: |
| 1 | 2 | 2 | 1 | 1 |
| 2 | 3 | 3 | 1 | 1 |
| 3 | 4 | 3 | 1 | 1 |
| 4 | 1 | 5 | 1 | 2 |
| 5 | 3 | 3 | 1 | 1 |
| 6 | 3 | 5 | 1 | 2 |
| 7 | 2 | 4 | 1 | 2 |
| 8 | 4 | 1 | 1 | 3 |
| 9 | 3 | 1 | 1 | 3 |
| 10 | 2 | 2 | 2 | 3 |

The table above shows the 10 subjects (subj) assigned to four faculty members (fac).

Each of these subjects was randomly distributed to three blocks (blk) namely block 1, 2 and 3 . The type of the subject can either be 1 for lecture and 2 for laboratory classes. The number of hours (hr) varied from 1 to 5 hours for lecture classes and 2 hours for laboratory classes.

### 2.1. Faculty ratings

A sample faculty ratings of simple problem no. 2 is given in table 2 below.

Table 2: Faculty ratings for simple problem no. 2

|  | Faculty Member |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
| Period | 1 | 2 | 3 | 4 |
| 1st | 1 | 3 | 1 | 2 |
| 2nd | 3 | 2 | 2 | 2 |
| 3rd | 2 | 2 | 2 | 3 |
| 4th | 2 | 1 | 3 | 1 |

The faculty ratings for the period above varied from 1 to 3 . A rating of 3 means that the period is the most preferred by the faculty while ratings 2 and 1 are the average and the least preferred, respectively. There are two lecture and one laboratory rooms per period for simple problems while there are five lecture rooms for difficult problems and two for laboratory subjects. There are three models used in this study: Genetic Algorithms (GA), Binary Integer Programming (BIP), and Linear Programming (LP). The model that produced the feasible and optimum rating was the one to be considered the best.

### 2.2. Genetic Algorithms (GA) model

The algorithm randomly generated an initial schedule and assign a rating for each subject based on the rating provided by the faculty member. The algorithm checked that the schedule created satisfied the condition as required in the scheduling process. The sum of all the ratings were taken and used as incumbent solution. The reproduction operator was applied to the current population to generate a mating pool. The incumbent solution was set as the solution with the best value of the fitness function in the initial population. Crossover operator and mutation operator were applied to the tentative new population to create new population. The process stopped when the optimum value reached a plateau where the incumbent solution could no longer be updated by any of the possible population.

### 2.3. Binary Integer Programming (BIP) model

The lists of variables to be used in the formulation of the problems are the following:

$$
\mathrm{x}_{\mathrm{i}, \mathrm{j}}=\text { assignment for subject } \mathrm{i} \text { to period } \mathrm{j} .
$$

where: $\quad i=$ subject (10 subjects for simple problems and 90 for difficult problems)
$j=$ schedule ( $1^{\text {st }}$ period to last period, 4 periods for simple problems and 12 periods for difficult problems)

Objective Function. The objective function of the model is based on the following:

Maximize : $\quad \Sigma \mathrm{rx}_{\mathrm{ij}}$

Where: $\mathrm{r}=$ faculty rating for the class period

Constraints. The constraints of the model are the following:
A. Subject constraints
$\Sigma \mathrm{x}_{\mathrm{ij}}=1$
where $\mathrm{i}=$ subject
j = possible period of the subject
B. Faculty conflict constraints
$\Sigma \mathrm{x}_{\mathrm{ij}} \leq 1$
where $\mathrm{i}=$ subjects handled by the faculty member in a period
$j=$ period of the day
C. Block conflict constraints
$\Sigma \mathrm{x}_{\mathrm{ij}} \leq 1$
where $\mathrm{i}=$ subjects of the block in a period
$j=$ period of the day
D. Room availability constraints
$\Sigma \mathrm{x}_{\mathrm{ij}} \leq \mathrm{N}$
where $i=$ subjects in a period
$j=$ period of the day
$\mathrm{N}=$ available number of rooms in a period

This is to be done for lecture, laboratory 1 and laboratory 2 subjects. E. Integer constraints, This is for BIP model only

### 2.4. Linear Programming (LP) model

The Linear Programming model of the problem is the same as the BIP model above except that it doesn't include the integer constraints.

### 2.5. Selection of the best option

The solution that provided the feasible and optimum summation of ratings in the scheduling of all of the subjects among the three models (GA, BIP, and LP) was the one considered as the best option.

## 3. Result and Discussion

Only simple problem no. 2 was illustrated and discussed in detailed in this section. The remaining three simple problems no. 1,3 , and 4 together with difficult problem no. $5,6,7$, and 8 were only included in the summary.

### 3.1. Simple problem no. 2

The summary of output of GA, BIP, and LP models on simple problem no. 2 is listed in table 3 below.

Table 3: GA, BIP and LP Models Output of Simple Problem No. 2
a) GA output
b) BIP output

| subj | fac | hr | type | blk | start | end | Days | Rating |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :--- | :---: |
| 1 | 2 | 2 | 1 | 1 | 8 | 9 | ThS | 3 |
| 2 | 3 | 3 | 1 | 1 | 11 | 12 | ThS | 3 |
| 3 | 4 | 3 | 1 | 1 | 9 | 10 | TTh | 2 |
| 4 | 1 | 5 | 1 | 2 | 11 | 12 | TWThFS | 2 |
| 5 | 3 | 3 | 1 | 1 | 10 | 11 | MWF | 2 |
| 6 | 3 | 5 | 1 | 2 | 8 | 9 | MTWThF | 1 |
| 7 | 2 | 4 | 1 | 2 | 10 | 11 | TWThF | 2 |
| 8 | 4 | 1 | 1 | 3 | 10 | 11 | T | 3 |
| 9 | 3 | 1 | 1 | 3 | 11 | 12 | F | 3 |
| 10 | 2 | 2 | 2 | 3 | 8 | 10 | T | 3 |


| subj | fac | hr | type | blk | start | end | Days | Rating |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 2 | 2 | 1 | 1 | 10 | 11 | MW | 2 |
| 2 | 3 | 3 | 1 | 1 | 9 | 10 | TThS | 2 |
| 3 | 4 | 3 | 1 | 1 | 10 | 11 | TThS | 3 |
| 4 | 1 | 5 | 1 | 2 | 9 | 10 | TWThFS | 3 |
| 5 | 3 | 3 | 1 | 1 | 9 | 10 | MWF | 2 |
| 6 | 3 | 5 | 1 | 2 | 11 | 12 | MTWThF | 3 |
| 7 | 2 | 4 | 1 | 2 | 8 | 9 | MTWTh | 3 |
| 8 | 4 | 1 | 1 | 3 | 10 | 11 | M | 3 |
| 9 | 3 | 1 | 1 | 3 | 11 | 12 | S | 3 |
| 10 | 2 | 2 | 2 | 3 | 8 | 10 | S | 3 |

c) LP output

| subj | fac | hr | type | blk | start | end | Days | Rating | $\%$ | OPT |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :--- | :---: | :---: | ---: | ---: |
| 1 | 2 | 2 | 1 | 1 | 10 | 11 | MW | 2 | 0.5 | 1 |
| 1 | 2 | 2 | 1 | 1 | 8 | 9 | MF | 3 | 0.25 | 0.75 |
| 1 | 2 | 2 | 1 | 1 | 8 | 9 | TS | 3 | 0.25 | 0.75 |
| 2 | 3 | 3 | 1 | 1 | 9 | 10 | TThS | 2 | 1 | 2 |
| 3 | 4 | 3 | 1 | 1 | 10 | 11 | MWF | 3 | 0.25 | 0.75 |
| 3 | 4 | 3 | 1 | 1 | 10 | 11 | TThS | 3 | 0.75 | 2.25 |
| 4 | 1 | 5 | 1 | 2 | 9 | 10 | TWThFS | 3 | 1 | 3 |
| 5 | 3 | 3 | 1 | 1 | 9 | 10 | MWF | 2 | 1 | 2 |
| 6 | 3 | 5 | 1 | 2 | 11 | 12 | MTWThF | 3 | 1 | 3 |
| 7 | 2 | 4 | 1 | 2 | 8 | 9 | MTWTh | 3 | 0.75 | 2.25 |
| 7 | 2 | 4 | 1 | 2 | 8 | 9 | WThFS | 3 | 0.25 | 0.75 |
| 8 | 4 | 1 | 1 | 3 | 10 | 11 | M | 3 | 0.75 | 2.25 |
| 8 | 4 | 1 | 1 | 3 | 10 | 11 | W | 3 | 0.25 | 0.75 |
| 9 | 3 | 1 | 1 | 3 | 11 | 12 | S | 3 | 1 | 3 |
| 10 | 2 | 2 | 2 | 3 | 8 | 10 | F | 3 | 0.5 | 1.5 |
| 10 | 2 | 2 | 2 | 3 | 8 | 10 | S | 3 | 0.5 | 1.5 |
|  |  |  |  |  |  |  | Optimum/Total Rating | 27.5 |  |  |

The table above shows that the start, end, and day columns correspond to the start time and end time of the day for a given subject. The optimum/total rating is the total of the ratings provided by the faculty member to the subjects. The GA, BIP and LP output of simple problem no. 2 produced an optimum rating of 24, 27 and 27.5 respectively. The LP model had the highest value but some of the subjects were assigned to more than one fix schedule which is not allowed in scheduling process. These subjects are $1,3,7,8$, and 10 of table 3c. This confirms the statement of the author in [4] that LP uses the divisibility rule where the values of the decision variables are allowed to be fractions and need not be integers alone. One limitations of LP is divisibility where the decision variables are allowed to take non-negative integer as well as fractional values. However, we quite often face situations where the planning models contain integer valued variables [5]. The best option in this case is the BIP model because it produces a feasible scheduling of all the subjects with a higher total rating of 27 when compared to the rating of 24 for the GA model. This supports the study made by the author in [6] where the GA model gives a significant reduction in the amount of time required for course scheduling and the results are more acceptable by teachers. This also validates the study the author in [7] that integer programming model has advantages over other models for determining faculty teaching timetabling. The author in [8] also shows that the genetic algorithms are able to produce promising results for the timetabling problem.

### 3.2. Summary of output

3.2.1. Summary of output for simple problems. The table 4 below illustrates the summary of output of simple problems 1, 2, 3, and 4.

Table 4a: Summary of output of simple problems

| Model | 1 | 2 | 3 | 4 | Ave | Comments |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| GA | 22 | 24 | 22 | 23 | 22.75 | Feasible |
| BIP | 28 | 27 | 29 | 28 | 28 | Feasible |
| LP | 28 | 27.5 | 29 | 29 | 28.375 | Not Feasible |



Table 4b: Graphical Illustration of the Summary of Output of Simple Problems

Table 4 a and 4 b above summarizes the total and average ratings of the three models (GA, BIP, and LP) of simple problems $1,2,3$, and 4 . GA model produced a total ratings of $22,24,22$, and 23 with an average of 22.75. BIP model produced a total ratings of $28,27,29$, and 28 with an average of 28 . LP model had $28,27.5$, 29, and 29 with an average of 28.375 . Both GA and BIP models produced feasible solution but LP model produced infeasible solutions because some of the subjects were not scheduled as what was required in standard schedule arrangement. This left the BIP model as the best scheduling model because it produced a higher average rating than the GA model. The author in [9] asserts that the problem formulation of LP assumes that all decision variables can take on any non-negative value including fractional ones; (i.e., the decision variables are continuous). This assumption is violated when non-integer values of certain decision variables make little sense. In this case, it is appropriate to use integer programming. The result also corroborated with the study made by the author in [7] that integer programming has advantages over other models.

### 3.2.2. Summary of output for difficult problems

The table 5 below illustrates the summary of output of difficult problems 5, 6, 7, and 8 .

Table 5a: Summary of output of difficult problems

| Model | 5 | 6 | 7 | 8 | Ave | Comments |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| GA | 350 | 268 | 245 | 326 | 297.25 | Feasible |
| BIP | 378 | 387 | 329 | 355 | 362.25 | Feasible |
| LP | 393.39 | 410.03 | 362.72 | 395.02 | 390.29 | Not Feasible |

Table 5b: Graphical Illustration of the Summary of Output of Difficult Problems


Table 5a and 5b above summarizes the total and average ratings of the three models (GA, BIP, and LP) on difficult problems $5,6,7$, and 8 . GA model produced the total ratings of $350,268,245$, and 326 with an average of 297.25. BIP model produced the total ratings of $378,387,329$, and 355 with an average of 362.25 . LP model had 393.39, 410.03, 362.72, and 395.02 with an average of 390.29. Both GA and BIP models produced feasible
solution but LP model produced infeasible solutions because some of the subjects were not scheduled as what was required in standard schedule arrangement. This left the BIP model as the best scheduling model because it produced a higher average rating than the GA model. The result of LP validates the study of the author in [9] that the problem formulation of LP assumes that all decision variables can take on any value including fractional ones and it is appropriate to use integer programming when non-integer values of certain decision variables make little sense. The result of GA supports the study of author in [10] that GA algorithm is not an overall winner, but it is very robust in the sense that it deterministically gives satisfactory lower and upper bounds in reasonable computation time without particular tuning. The BIP result corroborates the study of author in [6] that real world university course timetabling model is both organizationally and computationally feasible with integer programming and indeed can be used to create substantially better timetables. The author in [11] also illustrated in his study that integer programming approach is well suited for solving the timetabling problem and the model provides constraints for a number of operational rules and requirements found in most academic institutions.

## 4. Conclusions

In simple problems, both GA and BIP models produced feasible solution while the LP model produced the highest total ratings but infeasible solutions to almost all of the problems because it uses the divisibility rule where subjects were assigned to more than one fix schedule. The BIP model produced a little higher average rating than the GA model and all of the subjects in the BIP model were assigned to the most preferred and averagely preferred schedule by the faculty members so that it was considered as the better model to simple problems.

In difficult problems, the LP model produced the highest total rating but not feasible for standard schedules because of divisibility problem where it allowed fractional output. Both GA and BIP models produced feasible solution but the BIP model was considered as the better model because it produced the higher average rating than the GA model and most of the subjects under the BIP model were scheduled in the preferred and most preferred schedule of the faculty members.

Since the LP model was not feasible and the BIP model produce a feasible and better total rating than the GA model then BIP was considered as the best model in faculty course scheduling optimization.

For as long as formulation of the needed function and constraints is possible and the solver can process them, then the BIP model can provides the feasible and optimal solution. An alternative to this model is the GA model that is capable of giving feasible solutions even in very complicated scheduling conditions. The LP model can be used as a basis of the correctness of the output provided by both the GA and BIP model because the optimum value that it gave was usually higher than these two models.

## 5. Recommendations

The study can be used by schools and universities for maximizing the scheduling of their subject. It is recommended that the two other studies namely, Faculty Course Assignment Optimization and the Faculty

Room Assignment Optimization should also be used by the school or university in order to maximize the impact of timetabling. The input data of this paper should make use of the result and output the Faculty Course Assignment Optimization and the output of this paper should be the raw data of the Faculty Room Assignment Optimization.

It is recommended that the BIP model should be use as a model for faculty course scheduling but in case the formulation of functions and constraints are already complicated that it can no longer be in the form of an equation, then an alternative is the GA model that is capable of giving feasible solutions even in very complicated scheduling conditions.

## Acknowledgements

The researchers acknowledge the help of Dr. Juanito Burguillos, the graduate program coordinator for his never ending support to the success of this paper.

## References

[1]. G. S. Tacadao. "A constraint logic programming approach to the course timetabling problem using eclipse". ADDU-SAS Graduate School Research Journal, vol. 8, no. 1, 2011.
[2]. S. Abdennadher and M. Marte. "University course timetabling using constraint handling rules". Applied Artificial Intelligence, vol. 14, issue 4, pp 311-325, Apr. 2000.
[3]. K. Schimmelpfeng, and S. Helber. "Application of a real-world university-course timetabling model solved by integer programming". OR Spectrum, vol. 29, issue 4, pp. 783-803, Oct. 2007.
[4]. S. I. Kanu, B. A. Ozurumba, and I. C. Emerole. "Application of Linear Programming Techniques to Practical Decision Making". Mathematical Theory and Modeling, vol.4, no.9, 2014.
[5]. Limitations of Linear Programming. Universal Teacher Publication. (http://www.universalteacherpublications.com/univ/ebooks)
[6]. Y. Wang. "Using genetic algorithm methods to solve course scheduling problems". Expert Systems with Applications, vol. 25, issue 1, p39, Jul. 2003.
[7]. R. H. Mc Clure and C. E. Wells. "A mathematical programming model for faculty course assignments". Decision Sciences, vol. 15, issue 3, pp. 409-420, 1984.
[8]. S. Yang, and N. S. Jat. "Genetic algorithms with guided and local search strategies for university course timetabling". IEEE Transactions on Systems, Man \& Cybernetics: Part C - Applications \& Reviews, vol. 41, issue 1, pp. 93-106, Jan 2011.
[9]. B. A. McCarl and T.H. Spreen. Applied Mathematical Programming Using Algebraic System, Texas, TX, Texas A\&M University - College Station, 2002.
[10]. G. Lach and M. Lubbecke. "Curriculum based course timetabling: new solutions to Udine benchmark instances". Annals of Operations Research, vol. 194, issue 1, pp. 255-272, Apr. 2012.
[11]. S. A. MirHassani. "A computational approach to enhancing course timetabling with integer programming". Applied Mathematics \& Computation, vol. 175, issue 1, pp. 814-822, Apr. 2006.


[^0]:    * Corresponding author.

