Collaborative Course Assignment Problem to Minimize Unserved Classes and Optimize Education Quality

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Abstract—This work proposes a collaborative course assignment model among universities. It is different from existing studies in educational assignment problems or course timetabling, where the scope is only within the institution or department. In this work, the system consists of several universities. A collaborative approach is conducted so that lecturers exchange is possible and conducted automatically. Each university shares its courses and lecturers. The optimization is conducted to minimize the unserved classes and improve education quality. The cloud-theory based simulated annealing is deployed to optimize the assignment. This model is then benchmarked with two non-collaborative models. The first model's objective is to minimize the unserved classes only. The second model's objectives are to minimize the unserved classes and improve education quality. The simulation result shows that the proposed assignment model is better in minimizing the unserved classes and improving education quality. The proposed model reduces 89 to 92 percent of the unserved classes ratio compared with the non-collaborative model.

Keywords—Course assignment problem; simulated annealing; collaborative model; online teaching; combinatorial problem

I. INTRODUCTION

Course assignment problem is a well-known study in operations research or optimization, especially in education. This popularity comes from the fact that course assignment is an important subject in educational operation. Moreover, circumstances in the educational operation are complex and diverse. First, the regulations in education among regionals or countries are different [1]. Furthermore, some institutions, especially universities, may have specific policies, needs, and objectives [1]. Although there is a generic form of course assignment model, many studies in this subject have specific circumstances that are transformed into objectives and constraints. The objectives include balancing workload [2], minimizing classes without lecturers [3], improving education quality [4], and so on.

Ironically, the scope of most existing studies in education timetabling and assignment problems is still within the university [5] or department [6]. On the other hand, lecturers are limited resources, like the timeslot and room. It means that these offered classes may not be conducted because no lecturers can handle these classes. The other condition is that these classes are still conducted, but the education quality may be dropped because less competent lecturers serve these classes.

On the other hand, the online class is common today. Due to the COVID-19 pandemic, schools, especially universities, are forced to swift from face-to-face to online interaction [7]. Although the online mechanism still has several weaknesses, such as the degradation of the learning outcomes and lack of interaction [7], the online class has several advantages. The location boundaries are not considered anymore if students and lecturers have reliable internet access [8], especially in rural or remote areas [9]. Moreover, physical rooms are not needed too.

This online class creates opportunities for inter-universities collaboration. Lecturer exchange becomes possible and easy. Some lecturers may teach courses that other universities offer. Through this collaboration, a university can offer courses to its students, although it does not have competent lecturers. A university also can open more classes even though its own lecturers are limited. On the other hand, a university also can provide its lecturers to handle courses or classes beyond their formal homebase. Moreover, assigning a course to a more competent lecturer can improve the education quality. Unfortunately, most studies in education timetabling or assignments were conducted based on physical classroom scenarios. These existing assignment models cannot be implemented directly to tackle this collaborative and online circumstance. Studies in operations research in the education area that promote collaboration and online learning are challenging and potential.

Based on this circumstance, this work proposes a collaborative course assignment model. In this work, the system consists of several universities. Each university shares its several classes and lecturers that can be assigned collaboratively. Each class has a specific course and timeslot. On the other hand, each lecturer can provide several courses and specific timeslots. The objective is to minimize the unserved classes and maximize the education quality.

This assignment model is then optimized by cloud-theory based simulated annealing (CSA). This algorithm is an improved version of simulated annealing. Rather than its original version, CSA is a population-based metaheuristic algorithm where every individual acts independently [10]. In the end, the best individual is chosen as the final solution.

This algorithm is chosen based on several reasons. First, the metaheuristic algorithm is popular in optimizing many operations research studies, especially assignment problems. This popularity comes from its approximate approach so that excessive computation can be avoided, although it may promise near-optimal or acceptable solutions [11]. Second, simulated annealing is a simple algorithm that can easily be implemented, improved, or modified to solve many optimization problems. Third, as a population-based algorithm, CSA is proven better than its original form in providing better solutions [10].

The contributions of this work are as follows:

1) This work proposes a course assignment model conducted collaboratively. The system consists of several universities rather than a single university or department, as it is common in most studies in education assignment or timetabling problems.

2) The proposed model is developed for online classes so that physical rooms are not needed. It is also different from most studies in education assignments or timetabling problems where their circumstance is the physical classroom.

This work is the continuation of our previous works in operations research in the education area. Both previous studies were conducted for joint course programs. The first study focused on the course timetabling [12], while the second focused on the faculty assignment [13]. The difference between this current work and the previous works is that the university's interest is considered in this work. In these previous studies, the existence of the universities as entities that provide lecturers and classes is not considered.

The remainder of this paper is organized as follows. The shortcoming studies in education assignment problems and course timetabling are explored in the second section. The proposed model that consists of both conceptual model, mathematical model, and the algorithm is explained in the third section. The simulation scenario and result are described in the fourth section. The more profound analysis conducted on the simulation result and findings are discussed in the fifth section. Finally, the conclusion and future research potentials are summarized in the sixth section.

II. RELATED WORK

In general, the assignment problem can be defined as allocating or assigning a certain number of objects to a certain number of other objects in the most optimal way [14]. The assignment problem consists of two components. The first component is the assignment [14], and the second component is the objective function [14]. An assignment is a combinatorial structure that consists of the link between a set of objects and another set of objects. The relationship between these sets of objects can be one-to-one, one-to-many, or many-to-many. On the other hand, the objective is the purpose of the assignment. The objective represents a valid measurement to evaluate the assignment's performance. Based on this concept, assignment problem becomes a part of operations research, and it is widely used in many areas, such as transportation [15], manufacturing [16], logistics [17], and so on.

In the education area, there are two well-known assignment problems. The first is the course timetabling problem [1]. The second is the faculty assignment problem [1]. In the course timetabling problem, a course will be allocated to certain timeslots and rooms. In the faculty assignment problem, the focus is plotting lecturers to the courses in the system. Both problems are at the operational level [1].

To date, there are huge numbers of studies conducting the assignment problem in the education area. This circumstance shows that operation research studies in education are still interesting. Besides, assignment problem in education is widely studied since there are various circumstances in the education institutions. This variety comes from several aspects, such as regulation, institutional objective, and local challenge [2]. Moreover, these studies are usually proposed based on certain specific objectives.

Many studies in the education assignment problem used metaheuristic algorithms as the optimization method. The use of metaheuristic algorithms comes from several reasons. First, the metaheuristic algorithm is a proven method used in many optimization studies. Second, this algorithm is proven to achieve a near-optimal solution with reasonable computation resources [11]. Third, the metaheuristic algorithm is a popular algorithm that has been studied extensively until now. To date, there are hundreds of metaheuristic algorithms that have been developed. Several well-known algorithms are also used in many education assignment problems, such as genetic algorithm [18], simulated annealing [19], tabu search [20], variable neighborhood search [6], genetic programming [21], and so on. Several shortcoming studies in the education assignment problems are summarized in Table I. In the last row, the positioning of this work is stated.

TABLE I. SHORTCOMING STUDIES IN EDUCATION ASSIGNMENT PROBLEM

Author	Scope	Physical Room	Optimization Method
[22]	department	needed	tabu search
[16]	department	needed	genetic algorithm, local search
[19]	department	needed	simulated annealing
[5]	department	needed	multi-agent, genetic algorithm
[20]	department	needed	variable neighborhood search, tabu search
[23]	university	needed	genetic algorithm
[6]	department	needed	tabu search, variable neighborhood search
[24]	university	needed	genetic algorithm
[25]	department	needed	tabu search, simulated annealing
[26]	department	needed	Monte Carlo search
[27]	department	needed	tabu search, iterated local search, simulated annealing
[21]	university	needed	genetic programming, genetic algorithm
this work	multiple universities	no needed	cloud-theory based simulated annealing

Table I shows that all shortcoming operation research studies in education still adopt a conventional approach. The scope of these studies is within a university or department. Several studies conducted certain classes, which is relatively small. Moreover, all these studies used physical rooms in the system.

This circumstance makes the existing assignment models cannot be implemented directly in the future education environment. The online collaborative system faces many different circumstances than the face-to-face noncollaborative system. In the future, online learning will become more popular. Moreover, the emergence of online learning makes collaboration among universities more possible. Based on this problem, proposing an assignment model that eliminates the physical boundaries and promotes a collaborative approach as in this work becomes very important and interesting.

The future online learning also promises more efficient teaching system. The university can provide more classes without creating more physical rooms or building so that it can save more capital expenditure for the development and operational expenditure related to the new buildings or rooms, such as electricity, water, cleaning service, furniture, maintenance, and so on. This cost reduction in the end can reduce the educational cost so that the institution will be more competitive. This cost reduction can also be used to tackle the cost increase in other posts, such as employee salary, internet, and so on so that the increase in the tuition fee can be avoided. The online learning also improves the teacher's movement time. In the face-to-face learning, the teacher must move from the current room to other room or from the current building to other building to teach other classes. Moreover, when the university has several separated locations, this movement wastes more time.

III. PROPOSED MODEL

This collaborative course assignment model consists of several entities: university, lecturer, and class. In the system, there are several universities. Each university has several lecturers and classes that will be shared in the system. It means a university still has a portion of its classes and lecturers that are not included in the system. These classes and lecturers will be managed exclusively by its homebase. Every lecturer can teach several courses, but their competence may be various among the courses. For example, a lecturer can teach database, algorithm, and object-oriented programming courses. His competence in teaching database is average but prominent in teaching algorithm and object-oriented programming. All lecturers have their available timeslots. A class is dedicated to a specific course and timeslot. In this model, students are already assigned to this class. Students are also abstracted and are assumed to take only one class per student. Fig. 1 illustrates the conceptual system. The blue dashed rectangles represent the universities, the blue circles represent the lecturers, and the yellow circles represent the classes.

The relationship between university, class, lecturer, course, and timeslot is as follows. The relationship between university and class is one-to-many. The relationship between university and lecturer is one-to-many. The relationship between lecturer and course is many-to-many. The relationship between lecturer

and timeslot is many-to-many. The relationship between class and lecturer is one-to-many. The relation between classes, courses, and lecturers are shown in Fig. 2. In Fig. 2, red circles represent the lecturers, blue circles represent the courses, and green circles represent the classes.

This proposed model has several hard constraints that cannot be violated [1]. These hard constraints are as follows.

- The number of universities, lecturers, and classes is predetermined [13].

- A lecturer cannot teach courses beyond his competency [13].

- A lecturer cannot teach multiple classes with the same timeslot [12].

- A lecturer cannot teach beyond his possible timeslots [12].

- Timeslot for every class is predetermined [13].

- A class cannot be conducted beyond the provided timeslots [12].

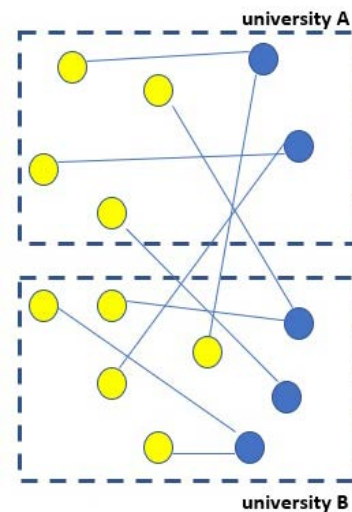- A class cannot be taught by multiple lecturers [13].
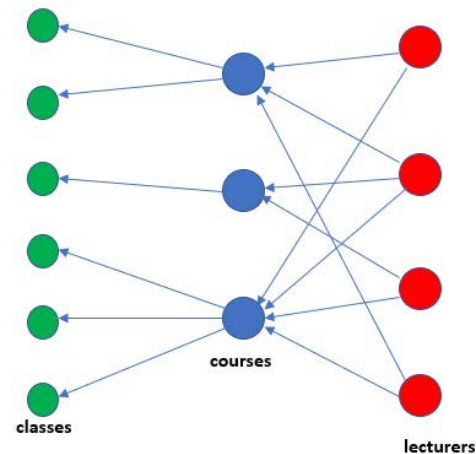

Fig. 1. Conceptual System.

Fig. 2. Relation between Lecturers, Courses and Classes.

This proposed model has two objectives. The first objective is to minimize unserved classes. It becomes the primary objective. The second objective is to maximize the education quality, meaning that classes will be taught by the most competent lecturer wherever possible. The internal lecturer is prioritized to accommodate the university's interest.

There are two types of assignments. The first assignment is the intra-university assignment. The second assignment is the inter-university assignment. In the intra-university assignment, a class will be allocated to the possible internal lecturer exclusively. In the inter-university assignment, a class will be allocated to any possible lecturer without considering the lecturer's homebase. The collaboration is conducted in the inter-university assignment.

This process is then optimized by using cloud-theory based simulated annealing. As a metaheuristic algorithm, it consists of two phases. The first phase is initialization. The second phase is iteration. Both intra-university assignments and inter-university assignments are conducted in the initialization. In the intra-university assignment, several courses may remain unallocated to a lecturer or unserved due to the mismatch problem. These unserved classes will be assigned in the inter-university assignment. Meanwhile, the iteration phase consists of only the inter-university assignment. As in all simulated annealing algorithms, the iteration consists of external and internal loops. In the external loop, iteration runs from the initial high temperature to the end low temperature with a certain decrease rate [10]. In the internal loop, iteration runs from the first iteration to the maximum iteration [10].

Neighborhood search is conducted to improve the solution. The solution candidate is generated near the current solution. If this candidate is better than the current solution, then this candidate replaces the current solution immediately. Otherwise, this candidate may replace the current solution with a certain probabilistic calculation to avoid local optimal trap.

The mathematical model is then developed based on this conceptual model. Several annotations used in this mathematical model are as follows. Meanwhile, the process in the proposed model is shown in Algorithm 1.

u	university
l	lecturer
L	set of lecturers
l_a	available lecturer
L_a	set of available lecturers
t	timeslot
T	set of timeslots
c	course
C	set of courses
s	class
S	set of classes
S_s	set of served classes
S_u	set of unserved classes
st	status
st_a	timeslot availability status
st_c	same course status
st_i	inter-university status
n	number of entities
f	fitness
o	objective
U	uniform random

i	iteration
i_{init}	initial iteration
i_{max}	maximum iteration
e	temperature
e_{init}	initial temperature
e_{end}	end temperature
Δe	temperature decrease rate
k	Boltzman constant
a	individual / solution
a_{best}	best individual
A	population
d	candidate

algorithm 1: collaborative course assignment model

```
1    output: a_best
2    //initialization
3    for x = 1 to n(A) do
4    begin
5      a_x = intra-university-assignment (L, S)
6      a_x = inter-university-assignment (L, S)
7    end
8    //iteration
9    e = e_init
10   while e > e_end do
11   begin
12     for i = i_init to i_max do
13     begin
14       for x = 1 to n(A) do
15       begin
16         d = neighborhood-search (a_x)
17         if f_1(d) < f_1(a_x) then
18           if f_2(d) > f_2(a_x) then
19             a_x = d
20           else
21             if U (0, 1) < exp ((f_2(d) > f_2(a_x))/e) then
22               a_x = d
23       end
24     end
25     e = e - Δe
26   end
27   a_best = min-sort (f_1(A))
```

The explanation of Algorithm 1 is as follows. The algorithm's output is to find the best individual or solution that consists of the best assignment in meeting the primary and secondary objectives. The initialization consists of intra-university assignments and inter-university assignments that are conducted serially. The outer loop is the loop that runs from the initial high temperature to the end low temperature. The temperature decreases gradually based on the temperature decrease rate. Then, the inner loop consists of iteration from the first iteration to the maximum iteration. In the iteration process, a neighborhood search based on the inter-university assignment is conducted. This neighborhood search is conducted to produce a candidate. Then this candidate is evaluated by two fitness functions that represent the objectives. The first function is minimization, while the second function is maximization. The candidate will replace the current solution immediately only if its performance is better than the current solution in both fitness functions. If the first candidate's first fitness is worse than the current solution, it is rejected immediately. Suppose the candidate is better than the current solution only in the first fitness function. In that case, it may replace the current solution based on a probabilistic calculation

where the fitness gap and the current temperature are considered. After all iterations end, the best solution is selected based on the primary objective.

As it is mentioned previously, the proposed assignment model has two objectives. The first objective is minimizing the unserved classes. The second objective is maximizing the education quality. The first objective is the primary objective, while the second objective is the secondary objective. These objectives are formalized by using (1) to (6).

$$o_1 = \min(f_1(a)) \tag{1}$$

$$f_1(a) = \frac{n(S_u)}{n(S)} \tag{2}$$

$$S_u = \{s \in S | st(s) = 0\} \tag{3}$$

$$o_2 = \max(f_2(a)) \tag{4}$$

$$f_2(a) = \frac{\sum_{n(S_s)} p(l,c)}{n(S_s)}, s \in S(l) \tag{5}$$

$$S_s = \{s \in S | st(s) = 1\} \tag{6}$$

The explanation of (1) to (6) is as follows. Equation (1) states that the first objective is to find a solution with minimum unserved classes. Equation (2) states that the first fitness function is obtained by dividing the number of unserved classes by the total number of classes. Equation (3) states that the unserved classes are classes that do not have lecturers. Equation (4) states that the second objective maximizes education quality. Equation (5) states that the education quality is obtained by dividing the summation of lecturers' competence related to the course and class with the number of served classes, and the class is taught by the lecturer. Equation (6) states that the served classes are classes that have lecturers.

The initialization process begins with the intra-university assignment process. Its mechanism is allocating every course to be taught by internal lecturers. This mechanism is conducted by collecting all internal lecturers who are available and competent to teach the selected course. Available means that the lecturer still has an available timeslot that is the same as the class timeslot. Competent means that the course taught in the class is on the lecturer's competence list. This mechanism is formalized by using (7) to (10).

$$st_i(s,l) = \begin{cases} 1, u(s) = u(l) \\ 0, else \end{cases} \tag{7}$$

$$st_a(s,l) = \begin{cases} 1, t(s) \in T(l) \land st(t(l)) = 0 \\ 0, else \end{cases} \tag{8}$$

$$st_c(s,l) = \begin{cases} 1, c(s) \in C(l) \\ 0, else \end{cases} \tag{9}$$

$$L_a(s) = \{l | st_i(s,l) = 1 \land st_a(s,l) = 1 \land st_c(s,l) = 1\} \tag{10}$$

$$l_{se}(s) = U(L_a(s)) \tag{11}$$

$$st(t(l)) = \begin{cases} 1, \exists s, t(s) = t(l) \land l(s) = l \\ 0, else \end{cases} \tag{12}$$

The explanation of (7) to (12) is as follows. Equation (7) states the internal status is 1 only if the class and lecturer are in the same university. Equation (8) states that the availability

status is 1 only if the class timeslot is within the lecturer's timeslot and the related lecturer's related timeslot is still available (open). Equation (9) states that the competence status is 1 only if the course in the class is within the lecturer's course list. Equation (10) indicates the set of available lecturers for the class. A lecturer is available if it meets all three statuses. Equation (11) states that the lecturer is selected randomly within the set of available lecturers. Finally, the timeslot status of the lecturer is set 1 if there exists a class in which the timeslot is the same as the lecturer's timeslot, and it is taught by the lecturer as indicated in (12).

The second step is the inter-university assignment process. This step is conducted only for classes that have not been assigned yet after the first step ends. In this step, the university status is not considered anymore. It means that a class can be taught by any available lecturer in the system. This process is formalized by using (13).

$$L_a(s) = \{l | st_a(s,l) = 1 \land st_c(s,l) = 1\} \tag{13}$$

Equation (13) shows that only two parameters determine the availability of a lecturer. The first parameter is the availability status, which is determined by using (8). The second parameter is the competence status determined by using (9). Finally, the lecturer is selected by using (12), where the set of available lecturers is determined by using (12).

There are several notes due to the initialization phase. First, this phase does not guarantee that there are no unserved classes. Second, the education quality determined by using (5) has not been optimized.

These notes become the reason to conduct the optimization process through iteration by using cloud-theory-based simulated annealing. In this algorithm, neighborhood search is conducted to improve the current solution. This search follows the inter-university assignment. This search is conducted by selecting several classes randomly. If there exists classes within these selected classes assigned to certain lecturers, then the lecturer-class link will be reset. Finally, the inter-university assignment is conducted for all unserved classes.

IV. SIMULATION AND RESULT

The proposed model is then implemented into a simulation to evaluate its performance. In this simulation, a certain number of universities are created. Then, a certain number of lecturers and classes attached to the universities are also created. Every class is conducted for a specific course within a specific timeslot. After these three entities are created, then the simulation runs to allocate these classes to a certain lecturer. The classes' course, lecturers' timeslot, lecturers' course, classes' university, and lecturers' university are generated randomly and follow a uniform distribution.

In this simulation, there are adjusted parameters and observed parameters. The observed parameters are the unserved classes ratio and the education quality ratio. The unserved classes ratio is a ratio between the number of unserved classes and the total classes. The education quality ratio is the average lecturer's competence score among the served classes. Meanwhile, the default value of the adjusted parameters is shown in Table II.

TABLE II. PARAMETERS' DEFAULT VALUE

Parameter	Default Value
$n(u)$	5
$n(C)$	20
$n(C(l))$	4
$n(S)$	200
$n(L)$	$n(S) / 2$
$n(T)$	15
$n(T(l))$	7

There are three simulations. The first simulation is conducted to observe the relation between the number of classes and the observed parameters. The second simulation is conducted to observe the relation between the number of lecturer's timeslot and the observed parameters. The third simulation is conducted to observe the relation between the number of courses conducted by a lecturer and the observed parameters.

The reason of choosing these parameters is as follows. The number of classes, lecturer's timeslot, and lecturer courses are resources that are easily to improve. In the online education environment, university can add more classes without creating new rooms or building which are necessary in the face-to-face teaching environment. The number of lecturer's timeslot is also easy to manage. Even though the total timeslot in a week is fixed, the number of lecturer's timeslot can be improved in several ways if it does not surpass the total timeslot. First, timeslots for the collaborative teaching can be increasing by reducing timeslots assigned for the non-collaborative teaching. Second, several lecturer's non-teaching activities can be shifted outside the teaching timeslots window. The number of lecturers courses is also can be improved easily if the teacher has enough preparation for the new course assignment, especially the courses that are near the current assignment. For example, lecturer that teaches algorithm course can also be assigned to teach other programming related courses, such as object-oriented programming. On the other hand, lecturer that teaches artificial intelligence can also be assigned to teach machine learning and deep learning courses.

This proposed model is benchmarked with two non-collaborative assignment models, in which both models are concerned with minimizing the unserved classes. There is a difference between the first model and the second one. The first model's objective is only to minimize the unserved classes. The second model is not only concerned with minimizing the unserved classes but also with maximizing the education quality. The first model is adopted based on the model proposed by Arratia-Martinez et al [3].

Meanwhile, the second model is adopted based on a model proposed by Wicaksono and Wisesa [28], where education quality is prioritized. But the second model is improvised so that the unserved classes are considered too. Moreover, the circumstance is also modified to be comparable to the proposed model. In this simulation, both models use cloud-theory-based simulated annealing too. They are fairly compared because the purpose of this simulation is not to compare the metaheuristic algorithms but to compare the collaborative approach with non-collaborative ones.

The first simulation is conducted to observe the relation between the number of classes and the observed parameters. The number of classes ranges from 150 to 250 with 20 step size. Other adjusted parameters are set to default. The result is shown in Fig. 3.

Fig. 3a shows that in general, the increase of the number of classes makes the decrease of the unserved classes ratio. It occurs in both non-collaborative models. On the other hand, the proposed model produces a zero unserved classes ratio due to this scenario. It occurs when the number of classes ranges from 150 to 250 units. It means that the proposed model outperforms both non-collaborative models in this simulation. Comparing both non-collaborative models, the first model is better than the second one in creating a lower unserved class ratio.

Fig. 3b shows that the number of classes does not affect the education quality ratio. The education quality ratio tends to be stagnant in all number of classes. This circumstance occurs in all models. Comparing among models, all models are competitive. Meanwhile, the second non-collaborative model is the best one with a very narrow gap. The performance of the proposed model and the first non-collaborative model is almost equal.
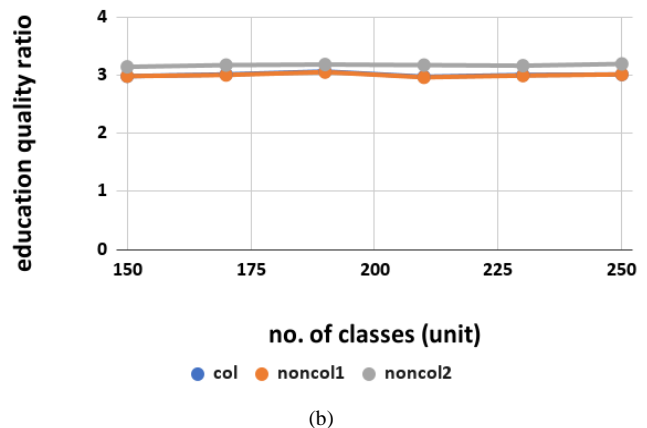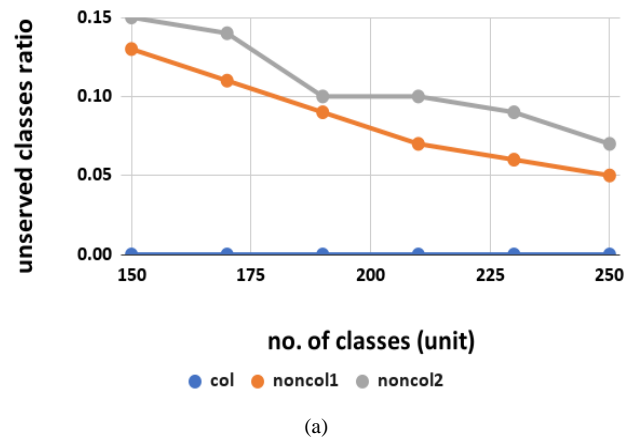

(a)

(b)

Fig. 3. Relation between the Number of Classes and Observed Parameters: (a) Unserved Classes Ratio, (b) Education Quality Ratio.

The second simulation is conducted to observe the relation between the number of lecturer's timeslots and the observed parameters. The number of lecturer's timeslots ranges from 4 to 8 with 2 step size. Other adjusted parameters are set to default. The result is shown in Fig. 4.
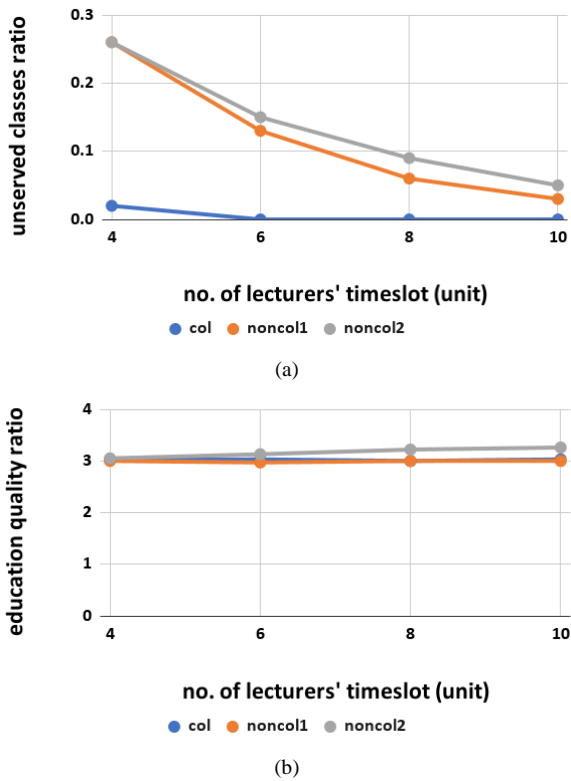

(a)

(b)

Fig. 4. Relation between the Number of Lecturers' Timeslot and Observed Parameters: (a) Unserved Classes Ratio, (b) Education Quality Ratio.

Fig. 4a shows that the increase of the number of lecturers' timeslot has made the unserved classes ratio decrease. It occurs in all models. Comparing among models, the proposed model performs as the best model. In the beginning, the unserved classes ratio is already very low. Then, the proposed model produces a zero unserved classes ratio when the number of lecturers' timeslot is higher than or equal to 6 timeslots. Meanwhile, the unserved classes ratio decreases significantly due to the decrease in the number of lecturers' timeslot but never reaches zero unserved classes ratio. In the beginning, the unserved classes ratio of the proposed model is only 8 percent of the non-collaborative models. It can be said that the proposed collaborative model reduces the unserved classes ratio by 92 percent relative to the non-collaborative models. The first non-collaborative model is better than the second non-collaborative model. The gap between these two non-collaborative models becomes wider due to the increase in the number of lecturers' timeslot.

Fig. 4b shows that the increase of the lecturers' timeslot creates different responses depending on the model. The education quality ratio tends to be stagnant for the proposed model and the first non-collaborative model. Meanwhile, the education quality ratio tends to increase less significantly due to the increase of the number of lecturers' timeslot for the

second non-collaborative model. The performance is almost equal between the models, but the second non-collaborative model has little advantage.

The third simulation is conducted to observe the relation between the number of lecturer's courses and the observed parameters. The result is shown in Fig. 5. The number of lecturer's courses ranges from 2 to 6 with 2 step size. Other adjusted parameters are set to default.

Fig. 5a shows that the number of lecturers' courses is inversely proportional to the unserved classes ratio. It occurs in all models. Comparing among models, the proposed model performs as the best model. In the beginning, the proposed model creates a very low unserved classes ratio. Then, the proposed model creates a zero unserved classes ratio when the number of lecturers' courses is higher than or equal to 4. Meanwhile, the first non-collaborative model performs better than the second non-collaborative model. In the beginning, the unserved classes ratio of the proposed model was only 11 percent of the non-collaborative model. It means that the proposed model reduces the unserved classes ratio of the non-collaborative model to 89 percent.

Fig. 5b shows that the increase in the number of lecturers' courses does not significantly affect the education quality ratio. The education quality ratio tends to be stagnant for the proposed model and the first non-collaborative model. Meanwhile, the education quality ratio increases less significantly for the second non-collaborative model.
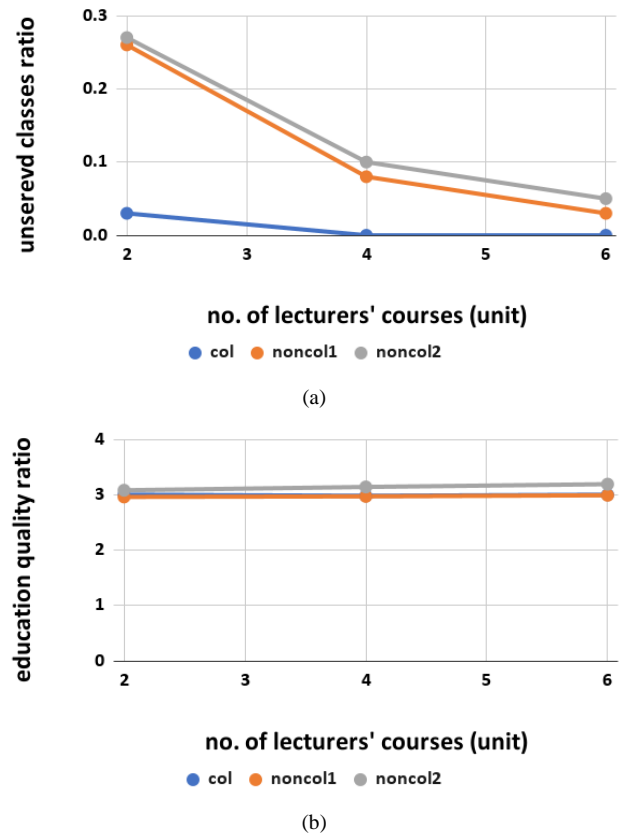

(a)

(b)

Fig. 5. Relation between the Number of Lecturers' Courses and Observed Parameters: (a) Unserved Classes Ratio, (b) Education Quality Ratio.

V. Discussion

There are several findings due to the simulation result. The proposed collaborative model is better in minimizing the unserved classes. This proposed model becomes the best model compared with both two non-collaborative models. The proposed collaborative model is competitive enough in maximizing the education quality. Meanwhile, the education quality among models tends to be equal.

All three adjusted parameters are inversely proportional to the unserved classes. The reason is as follows. The higher number of classes with the same number of courses makes the matching process easier. It is because in this simulation, the number of lecturers is proportional to the number of classes. The increase of the lecturers' timeslot also minimizes the unserved classes. It is because the lecturers' availability increases too due to the class predetermined timeslot. The increase of the lecturers' courses also minimizes the unserved classes. But the number of lecturers' timeslot is more significant than the number of lecturers' courses.

The simulation result shows that all three adjusted parameters do not significantly affect education quality. The reason is that education quality is put as the secondary objective during the optimization process. The new solution can replace the existing solution only if its unserved classes ratio is lower. It means that the unserved classes ratio is more prioritized than education quality. It is different from the model that adopts other multi-objective methods, such as non-dominated sorting, as it is used in the non-dominated sorting genetic algorithm (NSGA II) [29] or weighted sum method [30]. In these two methods, all criteria are treated equally. The NSGA II promises pareto optimal [29]. In NSGA II, a solution is better than another if it meets two rules. The first rule is that this solution is better or equal to its opponent in all parameters [29]. The second rule is that this solution is better than its opponent, at least in a parameter [29]. Meanwhile, the weighted sum method is simpler. It is conducted by aggregating all weighted parameters [30]. The weight represents the priority.

Finally, the result shows that the collaborative model tends to be better than the existing non-collaborative models as it becomes the main reason for this work. The collaborative model is proven to improve the quality of service in the context of reducing the unserved classes. The unserved class has become the classic issue in many operations research studies in the education area. In general, despite the chosen optimization method, reducing unserved classes is conducted by increasing the resources (rooms, lecturers, timeslots, and so on). This work shows that the unserved classes can be minimized without increasing resources through collaboration. This collaboration allows idle resources to be transferred to the more needed demand. But this collaboration occurs due to the existence of online learning so that the class can be conducted without physical appearance. This result also strengthens the statement that collaboration or resource sharing can give comparative advantage [31], for example, in improving the utility rate of resources and efficiency [32].

This theoretical result can be used as basis for the practical use in the online collaborative education system. Every institution (university) can focus on the three aspects (number of classes, number of lecturer's timeslot, and number of lecturer's courses) to reduce the unserved classes. University can shift more classes provided in its own institution to be conducted in the collaborative system. It means that the opportunity of these classes will be conducted by lecturers from outside of the institution will be higher. Reciprocally, the institution can push more lecturers to join the collaborative system of more timeslots to be allocated in the collaborative system. Finally, every institution should encourage its lecturers to conduct more courses. In the current non collaborative system, a lecturer is difficult to teach other courses because these courses have been assigned to the colleagues. On the other side, in the collaborative system, the opportunity to teach beyond the lecturer's traditional courses is wider. This circumstance gives benefit for both parties. The institution will benefit by the reduction of the unserved classes. The lecturers will benefit by improving their skill, competence, and experience.

VI. Conclusion

This work has demonstrated that the proposed collaborative model has met the objective of minimizing the unserved classes and maximizing the education quality. The simulation result shows that the proposed collaborative model outperforms both non-collaborative models in minimizing the unserved classes significantly. The proposed model reduces 89 to 92 percent of the unserved classes ratio compared with the non-collaborative models. On the other hand, the proposed collaborative model performs equally with the non-collaborative models to maximize education quality. The reason is that in this work, the unserved classes are more prioritized than the education quality, so minimizing the unserved classes becomes the primary objective while maximizing the education quality becomes the secondary objective.

This work has several limitations so that it can become the baseline for future improvements. This work has not discussed the financial aspect due to the collaborative approach. In general, any proposed approach should give financial incentives. Without financial incentives, universities will hesitate to adopt any collaborative approaches. Based on it, it is potential and important to propose a financial model that follows the collaborative assignment model. This financial incentive can be obtained through the efficiency of reducing the unserved classes without additional resources, i.e., lecturers or rooms. It means that this saving can be distributed to the existing lecturers and institutions. Second, this financial incentive should be transferred from the institution who owns the class to the institution whose lecturer conducts this class. This financial model should give win-win solution for both institutions.

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