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LONG PAPER

Developing a context-aware ubiquitous learning system based on a hyper-heuristic approach by taking real-world constraints into account

Peng-Yeng Yin · Kuo-Hsien Chuang · Gwo-Jen Hwang

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Abstract In a context-aware ubiquitous learning environment, learning systems are aware of students' locations and learning status in the real world via the use of sensing technologies which provide personalized guidance or support. In such a learning environment that guides students to observe and learn from real-world targets, various physical world constraints need to be taken into account when planning learning paths for individuals. In this study, an optimization problem is formulated by taking the relevance of real-world learning targets and the environmental constraints into account when determining personalized learning paths in the real world to maximize students' learning efficacy. Moreover, a hyper-heuristic approach is proposed to efficiently find quality learning paths for individual students. To evaluate the performance of the proposed approach, the teachers' feedback was collected and analyzed based on the learning activities conducted in an elementary school natural science course; in addition, the performances of the proposed algorithm and other approaches were compared based on a set of test data.

Keywords Context awareness · Ubiquitous learning (u-learning) · Genetic algorithm · Ubiquitous computing · Hyper-heuristic

P.-Y. Yin · K.-H. Chuang
Department of Information Management, National Chi Nan University, Nantou 54561, Taiwan

G.-J. Hwang (✉)
Graduate Institute of Digital Learning and Education, National Taiwan University of Science and Technology, Taipei 106, Taiwan
e-mail: gjhwang.academic@gmail.com

1 Background and motivation

In the past decade, researchers have applied mobile devices, wireless networks and ubiquitous computing technologies (e.g., sensing devices or sensor networks) to educational settings. They have aimed to develop learning environments that guide and support students' learning in the real world [19, 27]. With the help of these technologies, the students' learning space is no longer limited to classrooms; moreover, it is possible to provide personalized learning guidance to individual students [15]. Such a technology-enhanced learning approach that employs mobile, wireless communication and sensing technologies to support students' learning in real-world contexts has been called "context-aware ubiquitous learning" or "contextual mobile learning" by researchers [6, 12, 19]. Various applications have revealed the success of this approach by situating students in well-designed real-world contexts to observe, probe, and collect data to investigate issues specified by teachers. For example, Akkerman et al. [1] conducted a historical learning activity based on a mobile game approach with GPS (Global Positioning System) and reported the benefits of such an approach in terms of improving the students' learning motivation [1]. Recently, Chen and Huang [6] conducted a context-aware ubiquitous learning activity in a museum with RFID (Radio-frequency identification) and found that the approach benefited the students with regard to improving their learning achievement and attitudes [6]. Recently, Hwang et al. [16] also reported the effectiveness of conducting Mindtool-based in-field learning activities with smartphones and QR-codes [16].

Researchers have further indicated that such a sensing technology-enhanced mobile learning approach enables the learning system to more actively guide students to learn in the real world [19, 21]. On the other hand, several studies have pointed out the difficulty of arranging learning activities for guiding students to learn the right thing in the right place at the right time [10, 17]. Without a proper learning guidance plan which takes the features of learning contents and the parameters of real-world environments into account, students' learning performance could be significantly affected when they are guided to learn from the contexts that combine both real-world and digital-world resources [20]. Therefore, it becomes an important and challenging issue to propose effective and efficient methods of planning physical paths which guide individual students to learn based on multiple criteria, including the relationships between the associated concepts of the real-world learning targets and the constraints of the real-world environment.

Most of the previous studies on learning path optimization problems mainly focused on the provision of personalized learning paths in computer-based or web-based learning environments, in which a learning path represents a learning sequence for guiding the students to learn a set of digital learning contents related to a learning task or issue [8]. In such a path optimization problem, students' knowledge levels, computer-based or web-based learning behaviors and personal factors are usually the criteria to be considered [7, 18, 30].

However, the constraints and factors to be taken into account in a path optimization problem for learning in the physical world are quite different. Previous studies have indicated that in addition to the relationships between the concepts or knowledge represented by the physical learning targets, the number of students is the key factor that could significantly affect the students' learning performance, owing to the physical constraints of real-world positions [11, 12, 34]. Researchers have further indicated the importance of controlling the number of students in individual physical positions to avoid affecting their learning performance [10, 17, 35].

To cope with this problem, a learning guidance approach based on a physical path optimization algorithm is proposed for developing personalized context-aware u-learning systems by taking the relevance of physical learning targets and the number of students who visits the same targets into consideration. The QR-code technology is used to confirm the locations of individual students in the real world, such that the learning system is able to guide the students to learn following the optimized learning paths.

2 Objectives and problem definition

Figure 1 shows a context-aware u-learning environment, which is an ecology area for conducting in-field learning activities for the natural science course in an elementary

Fig. 1 Real-world learning environment for conducting context-aware u-learning activities on a school campus

Fig. 2 Structure of the context-aware u-learning environment

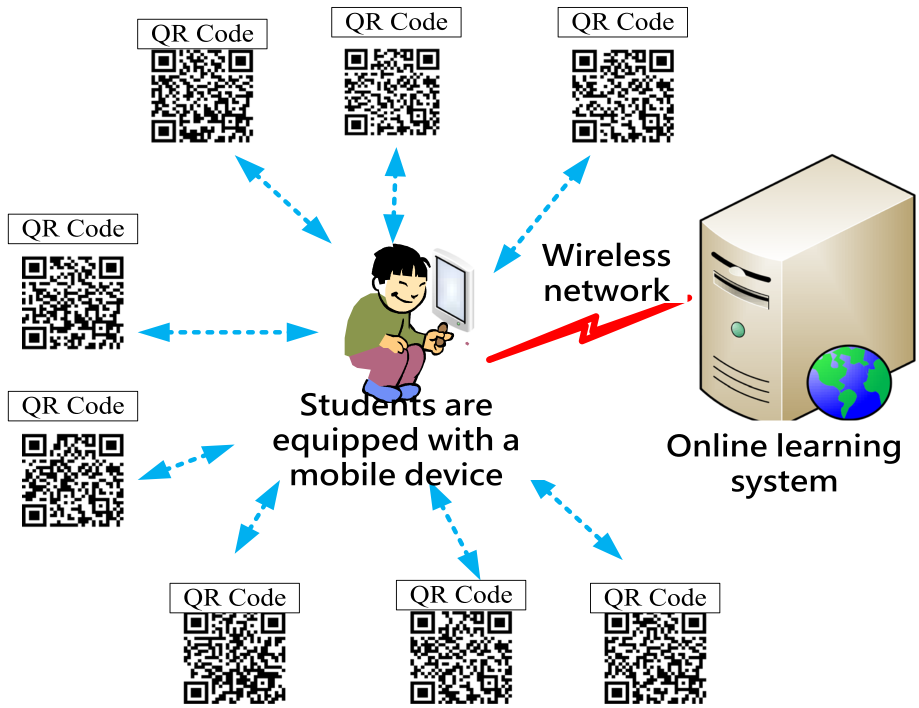


Fig. 3 Interface of the learning target and task

school in Taiwan. There are many plants raised in this ecology area. The u-learning system was developed with JAVA Eclipse. In the field trip, students are equipped with a 7-in. tablet computer; moreover, QR-codes are used so that the mobile learning system can confirm the locations of individual students. The students are asked to observe the plants and complete the learning tasks specified by the teachers using a mobile device with wireless communication facilities.

Figure 2 shows the structure of the context-aware u-learning environment, which consists of a server for executing the online learning system, a wireless network for supporting interactions between the students and the learning system and the real-world learning targets (e.g., plants) with QR-code tags. During the in-field learning activities, the students are guided by the learning system in the real-world learning environment to complete a set of specified learning tasks via observing the target plants and identifying the features of the plants.

Figure 3 shows the interface of the u-learning system. It guides students to find the learning targets following a predetermined sequence by showing them the name and appearance of the targets. When arriving at the location of a learning target, students are asked to confirm their location by taking a photo of the QR-code tag on the target. After confirming that the code is consistent with the learning target, the learning system starts to present question-based learning tasks and supplementary materials to the students.

The traditional in-field learning activity is conducted in a paper-based fashion. In other words, the students receive a learning item sheet and are requested to answer the question items and compile their findings on the sheet during the learning activity. Such a learning activity lacks personalized guidance or support for the students' observation of the real-world objects. Some students might overlook the key features of the target objects or may not be able to complete the mission simply owing to insufficient guidance. It is anticipated that this form of learning activity suffers a number of disadvantages as described in the following.

First, each target object has different concepts represented by key features. The students might fail to comprehend the relationships among those target objects if they visit the target objects via an arbitrary learning path without any guidance. The students are likely to be disorientated in the learning process. Novak [26] indicated that learning is a continuous process which adds new information to the existing information repository [26]. If a learner can be guided to connect new information with the existing information, the learning process is called *meaningful learning*. In the past decades, researchers have addressed the importance of guiding students to learn in a meaningful and effective way, that is, to assist the students in learning new concepts based on relevant knowledge that has already been established [2, 4].

Second, researchers have found that learning performance is significantly deteriorated if too many people attempt to visit or learn about the same target object simultaneously [5, 11, 12, 25, 34]. This phenomenon is commonly seen when conducting learning activities in real-world environments such as museums, ecology gardens, or classrooms. It is imperative to constrain the size of the learner group attending the target object at the same time. As the target objects might have different physical characteristics and the location of the objects also imposes certain space constraints, the size of the learner group should be dependent on the learning targets. It is difficult for the students to self-organize learner groups of appropriate size if they are not provided with guidance.

This study addresses the capacity-constrained personalized learning path (CCPLP) problem in a context-aware u-learning environment, wherein the students are guided to observe the learning targets and complete their mission with support from the learning system via mobile devices (such as tablet PCs or smartphones), wireless communication, and sensor technology. Personalized support is provided to assist the students in completing their learning mission in the authentic learning environment. The time allowed for visiting any learning target is the same, so that the students who are observing different learning targets can start to learn about the next learning target at the same time. However, the maximal number of students simultaneously visiting one particular learning target should be no more than a specified capacity limit in order to maintain good quality learning.

The objective is to conduct the in-field learning activity in a more *effective* and *efficient* way. Provided the relevance degree for a student learning an object in immediate succession of another object is known a priori, it is beneficial to arrange a personal effective learning path for the student to learn the objects in an appropriate sequence such that the overall relevance degree gained is maximized. Moreover, the learning paths of all the students result in different learning groups visiting the objects. They should be planned in an efficient way which considers the size limit of the learning group for the objects, so that fewer students will be deterred from attending the next learning target. Under the assumptions and objectives noted, the

Table 1 Description of the notations used in the problem formulation

n	Number of students attending this context-aware u-learning course
m	Number of learning targets
Last_k	Number of time phases at the time when the k-th student finishes observing the last learning target
N	Maximal number of time phases for observing the learning targets, $N \geq m$
t	Time phase index on the learning path, $1 \leq t \leq N$
S_k	The kth student, $1 \leq k \leq n$
A_i	The ith learning target, $1 \leq i \leq m$
$\mathrm{R}(S_k, A_i, A_j)$	Relevance degree perceived by the kth student for learning target i in immediate succession of target j, $0 \leq R(S_k, A_i, A_j) \leq 1.0$
$L(S_k, j)$	Location of the jth learning target on the learning path for the kth student
$\mathrm{Num}(A_i, t)$	Number of students located at the ith learning target in the tth time phase
$\mathrm{Capacity}_i$	Maximal allowed number of students for studying the ith object simultaneously

mathematical formulation for the CCPLP problem is proposed as follows.

$$\text{Minimize} f = \alpha\left(\frac{\sum_{k=1}^{n}\text{Last}_k}{nm}\right) + \beta\left(\sum_{k=1}^{n}\sum_{j=1}^{m-1}\frac{[1 - R(S_k, L(S_k, j+1), L(S_k, j))]}{n(m-1)}\right) \quad (1)$$

Subject to

$$\text{Num}(A_i, t) \leq \text{Capacity}_i, \quad 1 \leq i \leq m, \quad 1 \leq t \leq N \quad (2)$$

The description for the used notations is given in Table 1. The objective function (1) contains two minimization terms for achieving the best efficiency and effectiveness of the in-field learning activity. The first term

$$\frac{\sum_{k=1}^{n}\text{Last}_k}{nm}$$

calculates the total number of time phases required by all students to finish learning all of the objects, where the denominator is used to normalize the value of this term to a unit range [0, 1]. The second term

$$\sum_{k=1}^{n}\sum_{j=1}^{m-1}\frac{[1 - R(S_k, L(S_k, j+1), L(S_k, j))]}{n(m-1)}$$

computes the total amount of irrelevance between two successive learning targets observed by any students in the learning activity, where the denominator also normalizes the term value within [0, 1]. Note that the relevance degree is converted to the irrelevance degree by subtracting the relevance value from one in order to fit the minimization objective framework. The relevance degree of two successive learning targets is asymmetrical and student-dependent. In other words, the relevance degree may be different when two successive learning targets on the learning path are exchanged, and the relevance degree between two successive learning targets may be different for distinct students. The parameters α and β represent the relative importance of the two objective terms, and we set $\alpha + \beta = 1.0$. Moreover, the constraint formula (2) stipulates that the number of students simultaneously observing any learning target should be bounded by a pre-specified capacity amount for the corresponding learning target. Thus, the purpose of this problem formulation is to minimize the average number of time phases consumed by any student to finish the learning activity and to carefully design personalized learning paths for individual students to maximize the collective relevance, while respecting the observer capacity constraint of the learning targets.

3 A hyper-heuristic approach to the CCPLP problem

The solution method to the CCPLP problem consists of two parts. The first part determines the student-dependent and asymmetric relevance degree between each pair of learning targets, while the second part identifies the quality learning paths for individual students based on the relevant information and the capacity constraint.

3.1 Determining the relevance between learning targets

In this stage, the repertory grid method is employed to assist the teachers and domain experts in determining the relevance between each pair of learning targets. The repertory grid method originated from Kelly's personal construct theory [22], which aims to elicit and analyze knowledge by identifying different concepts in a domain and distinguishing among them. In a repertory grid, the targets to be classified or identified are called "elements" and are placed in the columns on top of the grid. Experts compare the elements and identify their traits; the positive traits (e.g., "the leaf shape of the plant is long and thin") are placed to the left, and the opposite traits (e.g., "the leaf shape of the plant is round and thick") to the right. Each pair of positive and opposite traits becomes a "construct" and is used to describe the characteristics of the elements. In each cell in the grid, users are usually asked to fill in the degree or tendency of each element for the construct from 1 to 5 where 1 refers to a positive trait, 2 signifies a partially positive trait, 3 represents no tendency either way, 4 is a partially opposite trait, and 5 means an opposite trait. Table 2 shows a repertory grid with 18 elements that represent the plants on the school campus where the constructs (i.e., the positive traits C1, C2, …, C23 and the opposite traits C1′, C2′, …, C23′) are the features for identifying and distinguishing the plants.

After a repertory grid is developed, a relevance analysis formula is then invoked to analyze the relevance between the elements [9, 23]:

$$\text{Relevance}(E_A, E_B) = 1 - \frac{\sum_{i=1}^{N}|\text{RG}(E_A, C_i) - \text{RG}(E_B, C_i)|}{K-1} \times \frac{1}{N} \times 100\,\%$$

In this formula, N represents the number of learning targets, K represents the maximum rating scale ($K = 5$ in this study), and RG (E_A, C_i) represents the rating for learning target E_A and construct C_i. Table 3 shows the degree of relevance among the elements in Table 2 by applying the formula, where the number in bold numbers indicate self-relevance.

Table 2 The repertory grid of the target plants

	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	E12	E13	E14	E15	E16	E17	E18	
C1	1	1	1	1	1	1	1	1	1	5	5	5	5	5	5	5	5	5	C1′
C2	5	5	5	5	5	5	5	5	5	1	1	1	1	1	5	5	5	5	C2′
C3	5	5	5	5	5	5	5	5	5	5	5	5	5	5	1	1	1	5	C3′
C4	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	1	C4′
C5	1	1	1	1	5	5	5	5	5	5	5	5	5	5	5	5	5	5	C5′
C6	5	5	5	5	1	1	1	5	5	5	5	5	5	5	5	5	5	5	C6′
C7	5	5	5	5	5	5	5	1	5	5	5	5	5	5	5	5	5	5	C7′
C8	5	5	5	5	5	5	5	5	1	5	5	5	5	5	5	5	5	5	C8′
C9	5	5	5	5	5	5	5	5	5	1	1	1	1	5	5	5	5	5	C9′
C10	5	5	5	5	5	5	5	5	5	5	5	5	5	1	5	5	5	5	C10′
C11	5	5	5	5	5	5	5	5	5	5	5	5	5	5	1	1	5	5	C11′
C12	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	1	5	C12′
C13	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	1	C13′
C14	1	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	C14′
C15	5	1	2	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	C15′
C16	5	2	1	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	C16′
C17	5	5	5	1	5	5	5	5	5	5	5	5	5	5	5	5	5	1	C17′
C18	5	5	5	5	1	5	5	5	5	2	1	2	5	4	5	2	5	5	C18′
C19	5	5	5	5	5	1	2	1	5	2	5	5	5	5	1	5	1	5	C19′
C20	5	5	5	5	5	5	2	5	1	5	5	2	1	5	5	5	5	5	C20′
C21	5	5	5	5	5	5	5	5	5	5	5	5	5	1	5	2	5	5	C21′
C22	5	5	5	5	5	5	5	5	5	2	5	5	5	5	5	5	5	5	C22′
C23	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	2	5	5	C23′

Table 3 Relevance analysis results

	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	E12	E13	E14	E15	E16	E17	E18
E1	**100**	88	88	91	83	83	80	83	83	68	74	72	74	73	74	68	74	74
E2	88	**100**	98	88	79	79	77	79	79	65	71	68	71	70	71	65	71	71
E3	88	98	**100**	88	79	79	77	79	79	65	71	68	71	70	71	65	71	71
E4	91	88	88	**100**	83	83	80	83	83	68	74	72	74	73	74	68	74	83
E5	83	79	79	83	**100**	91	89	83	83	75	83	78	74	75	74	75	74	74
E6	83	79	79	83	91	**100**	96	91	83	75	74	72	74	73	83	68	83	74
E7	80	77	77	80	89	96	**100**	87	87	73	72	76	78	71	78	66	78	72
E8	83	79	79	83	83	91	87	**100**	83	75	74	72	74	73	83	68	83	74
E9	83	79	79	83	83	83	87	83	**100**	68	74	78	83	73	74	68	74	74
E10	68	65	65	68	75	75	73	75	68	**100**	92	90	86	78	75	707	75	68
E11	74	71	71	74	83	74	72	74	74	92	**100**	96	91	84	74	75	74	74
E12	72	68	68	72	78	72	76	72	78	90	96	**100**	96	82	72	73	72	72
E13	74	71	71	74	74	74	78	74	83	86	91	96	**100**	82	74	68	74	74
E14	73	70	70	73	75	73	71	73	73	78	84	82	82	**100**	73	76	73	73
E15	74	71	71	74	74	83	78	83	74	75	74	72	74	73	**100**	86	91	74
E16	68	65	65	68	75	68	66	68	68	70	75	73	68	76	86	**100**	77	68
E17	74	71	71	74	74	83	78	83	74	75	74	72	74	73	91	77	**100**	74
E18	74	71	71	83	74	74	72	74	74	68	74	72	74	73	74	68	74	**100**

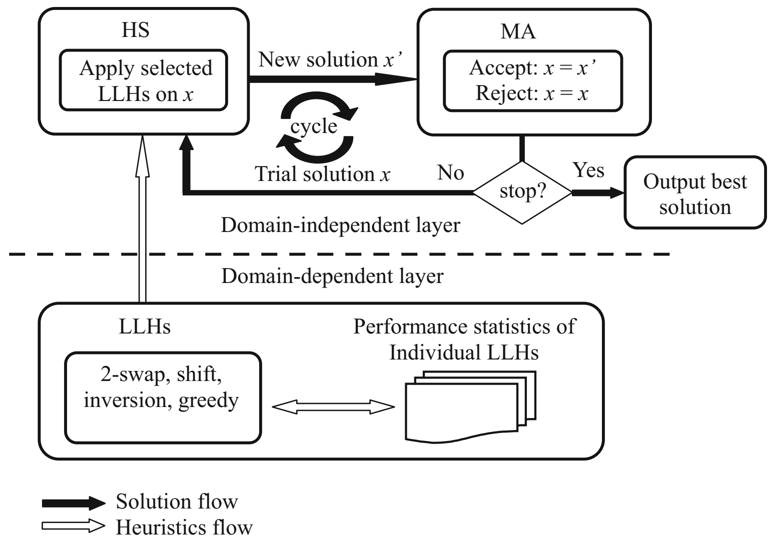


Fig. 4 Architecture of the hyper-heuristic framework

3.2 Determining the personalized optimal learning paths

After determining the relevance between learning targets, the optimal solution to the CCPLP problem based on the mathematical model of Eqs. (1) and (2) can be obtained by optimization approaches. In the following, a novel hyper-heuristic optimization method is proposed for deriving the optimal personalized learning paths.

3.2.1 Hyper-heuristic optimization framework

The hyper-heuristic framework [3, 13, 28, 29, 31–33] is a conceptual method that solves an optimization problem by selecting and combining lower-level heuristics (LLHs) to create a more effective form of optimization method. Figure 4 shows the architecture of the hyper-heuristic framework which consists of two layers: the domain-dependent layer and the domain-independent layer. The *domain-dependent layer* has a repository of lower-level heuristics (LLHs) which are designed according to the characteristics (such as the objectives and the constraints) of the addressed problem. The LLHs are primitive operations which can be applied to produce a new solution based on a given trial solution. There usually already exist a number of LLHs suited to the underlying problem. For example, the 2-swap, shift, and inversion are widely used LLHs for permutation-based combinatorial optimization problems, such as the CCPLP problem. On the other hand, the *domain-independent layer* contains the *heuristic selection* (HS) and the *move acceptance* (MA) methods, both of which can be implemented without knowing any domain knowledge of the problem. The HS method selects one or more LLH(s) from the repository based on the performance statistics. A new solution is produced by applying the selected LLH(s) to the current trial solution. The MA method makes the decision about whether to accept the new solution to replace the current trial solution. The hyper-heuristic framework iteratively performs the cycle of the HS and the MA methods until a stopping criterion is reached. The hyper-heuristic is flexible because new features can be augmented to HS and MA to make the resulting optimization method more effective. Due to the great success of evolutionary computation (EC), two well-known EC approaches are employed, the genetic algorithm (GA) [14] and simulated annealing (SA) [24], to implement the HS and MA components, respectively.

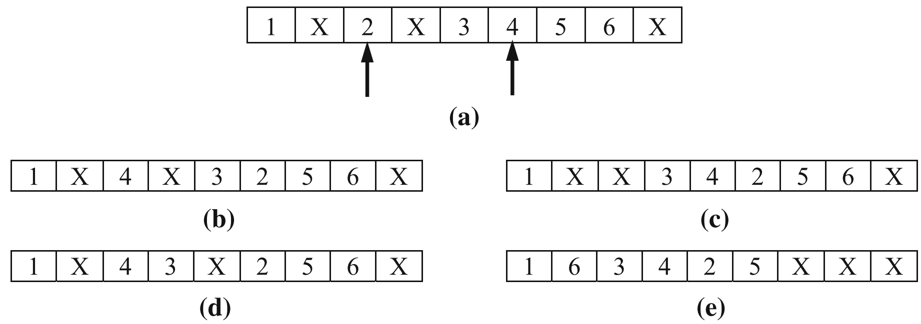
Table 4 Example solution of the scheduled learning paths of 6 objects for 30 students

		Time phase index								
		1	2	3	4	5	6	7	8	9
Student index	1	1	X	2	X	3	4	5	6	X
	2	2	3	X	4	X	1	X	6	5
	:					:				
	:					:				
	29	5	X	4	2	1	X	3	X	6
	30	2	3	X	6	5	4	X	1	X

3.2.2 Proposed lower-level heuristics

As noted, the 2-swap, shift, and inversion are widely used LLHs for permutation-based combinatorial optimization problems. In addition to the three LLHs relying on random perturbations, another greedy LLH which operates in a systematic procedure rather than in a random manner is proposed. A solution (the learning paths of all the students)

Fig. 5 Illustrations of the four proposed LLHs



to the CCPLP problem can be represented by an $n \times N$ matrix where n is the number of students and N is the maximal number of time phases. Table 4 shows an example solution for learning 6 objects by 30 students within 9 time phase units. The ith row corresponds to the personalized learning path arranged for the ith student. For the elements contained in each row, the number indicates the index of the learning object to which the student is attending, and symbol X denotes that the corresponding student has to wait at that time due to the capacity constraint. In order to produce a new solution, the LLHs used will randomly choose a number of students to alter the learning paths. Using the first student in Table 4 as an example, two reference positions are determined randomly for performing the LLHs, say, the 3rd and the 6th positions are chosen as shown in Fig. 5a. The operation of the proposed four LLHs is illustrated as follows.

The swap heuristic (denoted LLH-A) exchanges the values on the two random positions, resulting in the new learning path as seen in Fig. 5b. The shift heuristic (denoted LLH-B) circularly moves the elements, starting from the 3rd position and ending at the 6th position, to the left in one position. The new learning path obtained for the first student is shown in Fig. 5c. The inversion heuristic (denoted LLH-C) reverses the order of the elements starting from the 3rd position and ending at the 6th position. Figure 5d shows the new learning path obtained by applying LLH-C. In contrast to the previously noted three LLHs which rely on randomness, the greedy heuristic (denoted LLH-D) is performed in a systematic way. It intends to shorten the learning path as much as possible. For the learning path in Fig. 5a, the LLH-D heuristic swaps the right-most number and the left-most symbol X in this learning path if the resulting new learning path does not incur a violation of capacity constraints. This LLH-D heuristic is repeated until the learning path cannot be made any shorter. Figure 5e shows the new learning path obtained for the first student, and it is seen that the length of the learning path is shortened by two time phase units compared to the original path (note that the three X symbols at the end of this path do not account for the length because the student has finished learning all the target objects within the first six time phases).

3.2.3 *Employing GA as the HS method*

In this paper, the HS process is conceived of as an optimization task (selecting the best LLH(s) to perform) and employs GA as the proposed HS method.

The GA encodes a possible combination of the LLHs by a chromosome of genes. The crossover and mutation operations are applied to the chromosomes to reproduce the offspring (new combinations of the LLHs). The performance of each offspring is evaluated by applying the encoded LLHs to the current trial solution and thus obtains a new solution. The objective value f (Eq. (1)) of the new solution indicates the performance of the applied LLHs. However, some LLH combinations may result in an infeasible solution which violates the capacity constraint. This problem is resolved by adding an amount of penalty to the objective value of the infeasible solution, viz.

$$f \leftarrow f + \sum_{i=1}^{m}\sum_{t=1}^{N} \max\{0, \mathrm{Num}(A_i, t) - \mathrm{Capacity}_i\}, \qquad (3)$$

where the second term is a penalty measuring the overall amount of the violation.

The performance statistics for each offspring is tallied in the domain-dependent layer (see Fig. 4), and the natural selection of GA chooses the fitter offspring based on performance statistics to participate in the evolution of the next generation. Hence, every GA generation completes a cycle of the hyper-heuristic method. After undertaking a sufficient number of generations, the GA has learned the best LLH combination.

3.2.4 *Employing SA as the MA method*

The SA is applied as the preferred MA method in order to achieve a balance between random and greedy searches such that the hyper-heuristic is more likely to escape from the trap of local optimal learning paths. The SA follows the Metropolis criterion which accepts all improving solutions.

The worsening solutions are accepted according to a probability following the Boltzmann distribution which draws on two factors: a control temperature parameter T and the worsening amount Δ in solution quality. The temperature T is decreased by a ratio after every cycle of the hyper-heuristic, and this process is called *annealing* which makes the search to tend to accept arbitrary random moves at the beginning and gradually transit to only accepting improving moves at the end. The SA mechanism increases the probability that the hyper-heuristic used finds the global optimal learning path.

4 Evaluation and analysis

A pilot study was conducted in an elementary school natural science course to test the performance of the u-learning system. The participants were three teachers and 31 sixth graders. Before the field trip, a 20-min briefing was given to the participants to introduce the functions of the mobile device and the u-learning system. Following that, the students were guided by the u-learning system in the field to observe 12 target flowers, including *Pentas lanceolata*, *Stachytarpheta jamaicensis*, *Lantana camara*, *Saluia splendens*, *Synedrella nodiflora*, *Ixeris chinensis*, *Surinam calliandra*, *Bidens pilosa*, *Angelonia angustifolia*, *Torenia fournieri*, *Allamanda cathartica*, and *Bignonia chamberlaynii* following the learning sequence determined by the u-learning system. In the meantime, the three teachers were asked to observe the learning behaviors of the students; in addition, they were asked to experience the u-learning process in order to evaluate the performance of the u-learning system. The total time for the u-learning activity was 100 min. Following the experiment, the teachers were interviewed and the performances of the proposed algorithm and other approaches were compared based on a set of test data.

4.1 Feedback from the teachers

In the first stage, three experienced teachers (coded TA, TB, and TC) who had taught the natural science course for more than 5 years were interviewed. The teachers were asked to comment on the usefulness and quality of the u-learning approach in comparison with the traditional in-field learning from two aspects, that is, motivating students to learn and improving learning efficiency.

- Motivating students to learn

All of the three teachers shared the same opinion that the developed u-learning environment could promote the learning motivation of the students. They were surprised that the students seemed to be more involved in the learning activity than they had expected them to be. TA stated that, "It is obvious that the mobile device with wireless communication facilities can motivate the students since they are able to access the online resources and interact with the learning system during the field trip". TB indicated that, "The students are happy and excited when using the mobile devices to learn in the field. It is obvious that, in comparison with the traditional in-field learning, the students show much higher interest in observing the plants". TC stated that, "The u-learning approach is impressive. I can see that the students are happy and motivated to learn in the field. They like to use the mobile devices to access supplementary materials via the wireless network. They also like to collect data by taking photos of the target plants".

- Improving learning efficiency

The three teachers all agreed that the context-aware u-learning approach could benefit the students in terms of improving their learning efficiency owing to the guidance

Table 5 Performance statistics for LLH-A (swap)

Problem instance	Performance statistics					
	Mean	SD	Min	Max	Hit ratio (%)	CPU time
#1	0.4058	0.0211	0.3659	0.4492	100	0.18
#2	0.4052	0.0096	0.3861	0.4208	100	0.49
#3	0.4414	0.0105	0.4238	0.4746	100	0.44
#4	0.4022	0.0075	0.3884	0.4197	100	1.27
#5	0.4334	0.0070	0.4190	0.4470	100	1.83
#6	0.4732	0.0058	0.4626	0.4851	100	3.29
#7	0.5639	0.0024	0.5586	0.5697	100	10.79
#8	0.6130	0.0013	0.6106	0.6155	100	22.16
#9	0.6257	0.0009	0.6238	0.6279	100	48.84
#10	0.6599	0.0008	0.6576	0.6611	100	109.51

Table 6 Performance statistics for LLH-B (shift)

Problem instance	Performance statistics					
	Mean	SD	Min	Max	Hit ratio (%)	CPU time
#1	0.6194	0.0244	0.5587	0.6670	100	0.20
#2	0.6143	0.0146	0.5805	0.6419	100	0.53
#3	N/A	N/A	N/A	N/A	0	0.48
#4	0.6617	0.0084	0.6423	0.6777	100	1.39
#5	0.7047	0.0076	0.6858	0.7203	96.67	1.96
#6	0.7049	0.0049	0.6925	0.7151	100	3.41
#7	0.7273	0.0029	0.7224	0.7343	100	10.86
#8	N/A	N/A	N/A	N/A	0	22.84
#9	N/A	N/A	N/A	N/A	0	48.79
#10	N/A	N/A	N/A	N/A	0	108.35

provided in the field. TA indicated that, "In my memory, students always crowded around the same learning targets in the traditional in-field learning, which might significantly affect their learning performance. However, in this learning activity, it is found that the students observed the target plants following the guidance of the learning system. It can be seen that their learning efficiency is improved". TB also shared the same opinion that, "The guidance provided by the u-learning system helps the students to observe the plants without being affected by other students during the field trip, which not only increases the students' learning efficiency, but also improves their learning efficacy". TC further indicated that, "The u-learning system works like a personalized tutor for individual students. It helps students observe the plants and provides them with the supplementary materials in the right place and at the right time. There is no doubt that the students' learning performance is improved".

Table 7 Performance statistics for LLH-C (inversion)

Problem instance	Performance statistics					
	Mean	SD	Min	Max	Hit ratio (%)	CPU time
#1	0.4571	0.0190	0.4180	0.5009	100	0.19
#2	0.4468	0.0130	0.4229	0.4709	100	0.51
#3	0.5415	0.0153	0.5114	0.5710	100	0.47
#4	0.4894	0.0100	0.4649	0.5096	100	1.35
#5	0.5525	0.0079	0.5382	0.5746	100	1.92
#6	0.5830	0.0064	0.5691	0.5944	100	3.39
#7	0.6688	0.0025	0.6639	0.6759	100	10.83
#8	0.7115	0.0020	0.7073	0.7144	80	23.57
#9	N/A	N/A	N/A	N/A	0	49.22
#10	N/A	N/A	N/A	N/A	0	105.45

Table 8 Performance statistics for LLH-D (greedy)

Problem instance	Performance statistics					
	Average	SD	Min	Max	Hit ratio (%)	CPU time
#1	0.5247	0.0000	0.5247	0.5247	3.33	0.20
#2	N/A	N/A	N/A	N/A	0	0.60
#3	N/A	N/A	N/A	N/A	0	0.54
#4	0.5124	0.0141	0.4982	0.5265	6.67	1.29
#5	N/A	N/A	N/A	N/A	0	1.62
#6	N/A	N/A	N/A	N/A	0	2.90
#7	N/A	N/A	N/A	N/A	0	8.47
#8	N/A	N/A	N/A	N/A	0	20.37
#9	N/A	N/A	N/A	N/A	0	48.37
#10	N/A	N/A	N/A	N/A	0	104.27

4.2 Performance evaluation of the heuristic algorithms

In this section, simulations are conducted in order to evaluate the performance of each individual component of the proposed hyper-heuristic approach. The platform of the experiments is a personal computer with a Pentium Dual-Core 2.0 GHz CPU, 2 GB RAM, and 250GB hard disk with 7200-rpm access speed. The programs were coded in C# Language. Ten problem instances of various sizes were randomly generated. The number of learning targets ranged from 6 to 80, and the number of students was between 10 and 200. The hyper-heuristic algorithm was performed for 30 repetitive runs on each problem instance, and the performance statistics are reported in the following.

4.2.1 Performance of each LLH

Tables 5, 6, 7 and 8 tabulate the performance statistics for each LLH. The first column indicates the index of the problem instance. The next four columns correspond to the mean, standard deviation, minimum, and maximum of the objective value (Eq. 1) over the 30 repeated runs. As the CCPLP problem has a capacity constraint, the previous four statistics are measured for the runs in which the finally obtained solution is feasible. Hence, the hit ratio of successful runs (obtaining a feasible solution) is further reported in the Hit Ratio column. The last column gives the mean CPU time in seconds that each independent run takes.

The performance comparison of the four LLHs is summarized as follows. *First*, the LLH-A (swap) has the best performance in terms of producing quality objective value; the LLH-C (inversion) ranks in the second place followed by the LLH-D (greedy) and the LLH-B (shift). This is because successive swap operations can produce any

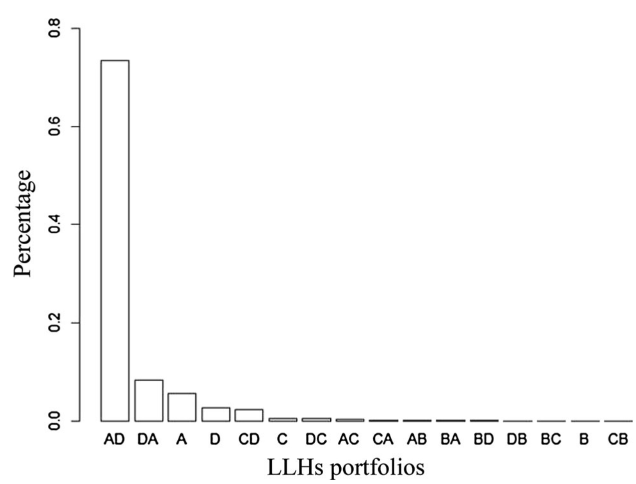


Fig. 6 Percentage of the portfolio using less than three LLHs for resolving problem instance #8

learning paths; however, the other three LLHs cannot. It is worth noting that although the four LLHs have different degrees of performance, they may compensate for each other. This initiates the authors' motivation for developing the hyper-heuristic to build the collaborations of the four LLHs. *Second*, for the hit ratio performance of producing feasible solutions, LLH-A successfully obtains a feasible solution for all runs on each problem instance, LLH-C can produce a feasible solution for at least 80 % of the repetitive runs on eight out of the ten instances, LLH-B achieves a hit ratio of at least 96.67 % on six out of the ten instances, and LLH-D has the lowest hit ratio. *Third*, the LLH-D (greedy) does not deal with the satisfaction of the capacity constraint (thus having the lowest hit ratio), but is designed for improving the objective value. The LLH-D has an imperative role in helping the other heuristics improve their solution quality when they are adopted under the hyper-heuristic framework, as will be noted. *Finally*, the four LLHs cost comparative CPU times on each problem instance because they all involve just simple operations.

4.2.2 Performance of the HS method

This section discusses whether the HS method can select the best portfolio (combination) of the LLHs at every hyper-heuristic cycle. In the experiment, it was found that most of the selected portfolios contained no more than two LLHs, indicating that the successive use of primitive, though effective, LLH portfolios is more advantageous than using complicated LLH portfolios. Figure 6 shows the percentage of the performed portfolio using less than three LLHs for problem instance #8, where letters A, B, C, and D represent LLH-A, LLH-B, LLH-C, and LLH-D, respectively. It is seen that the top four mostly used LLH portfolios which are compositions of A and D. This phenomenon conforms to the observations from the previous experiment on the single LLH performance where LLH-A achieves the highest performance and LLH-D can collaborate with the other LLHs to improve the solution quality. It is interesting to note that the percentage of execution of single A or D is also high because they can form AD or DA if they are executed in two successive cycles.

The implications from Fig. 6 are notable. The hyper-heuristic method provides a flexible framework which intelligently chooses effective LLH portfolios to achieve the maximum synergy. Consequently, the practitioners can focus on the design of the HS and the MA methods rather than on developing complicated LLHs which require intensive domain knowledge. The selection performed by the HS method has a high consensus with the performance evaluation of the individual LLHs. Moreover, the HS method can identify highly effective portfolios which may be overlooked by human experts. For example, LLH-D, when performed alone, has the lowest hit ratios in solving the problem instances (see Table 8), so it may be ignored by a domain expert. However, LLH-D is identified by the proposed HS method as being able to shorten the learning path in a greedy fashion and directly improves the objective value if it works in collaboration with other LLHs. The proposed HS method intelligently exploits this invisible clue and increases the probability of identifying the global optimal learning path.

4.2.3 Performance of the MA method

The proposed MA method adopts the SA to decide whether to accept a new solution to replace the current trial solution. The success of the SA depends on the control of the annealing process which gradually decreases the temperature and adapts the solution acceptance probability. The

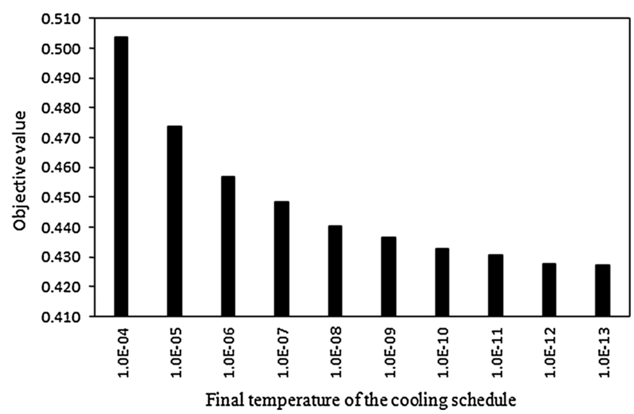


Fig. 7 Objective value obtained by the MA method as the final temperature of the annealing process decreases

Table 9 Performance statistics for the hyper-heuristic method

Problem instance	Hyper-heuristic					
	Mean	SD	Min	Max	Hit ratio (%)	CPU time
#1	0.3626	0.0059	0.3477	0.3739	100	0.44
#2	0.3980	0.0105	0.3782	0.4218	100	0.86
#3	0.4108	0.0082	0.3954	0.4256	100	0.83
#4	0.3950	0.0123	0.3782	0.4332	100	1.69
#5	0.3590	0.0037	0.3520	0.3681	100	2.37
#6	0.3685	0.0027	0.3649	0.3778	100	3.74
#7	0.3821	0.0017	0.3787	0.3874	100	12.09
#8	0.4265	0.0020	0.4229	0.4304	100	28.13
#9	0.4358	0.0015	0.4334	0.4392	100	67.27
#10	0.4652	0.0018	0.4621	0.4694	100	111.08

MA method is thus executed with various settings for the final temperature of the annealing process. Figure 7 shows the objective value obtained by the MA method as the final temperature of the annealing process decreases. It is observed that less objective value (i.e., higher quality) solutions can be obtained if the annealing process is conducted until the temperature is sufficiently close to zero. It is seen that the value of 1.0 E−13 is an appropriate setting for the last temperature in the annealing process, and the performance improvement becomes negligible when the final temperature further decreases.

4.2.4 Overall performance of the hyper-heuristic method

An evaluation of the overall performance of the proposed hyper-heuristic method, which intelligently takes advantage of the four LLHs by using the HS and the MA methods, was conducted. Table 9 lists the performance of the hyper-heuristic which is significantly better than those obtained by individual LLHs (see Tables 5, 6, 7, 8). It strongly supports the claim that it is beneficial to employ a hyper-heuristic approach rather than solve the problem by a single complicated heuristic. As a visual illustration, Fig. 8 shows the objective values obtained by the compared methods. It is seen that the hyper-heuristic obtains the least objective value compared with those obtained by individual LLHs on all of the test problems. The performance improvement is due to the fact that the hyper-heuristic selects and performs the best LLH portfolios at every cycle and then applies the move acceptance function to create a search course which effectively explores the solution space. Moreover, as shown in Fig. 9, the consumed CPU time for the compared methods increases as the problem size increases. All of the four LLHs require comparable computational time to accomplish a complete run. The hyper-heuristic applying the HS and the MA methods requires a little extra computational time, which resulted in the significant performance gains as shown in Fig. 8.

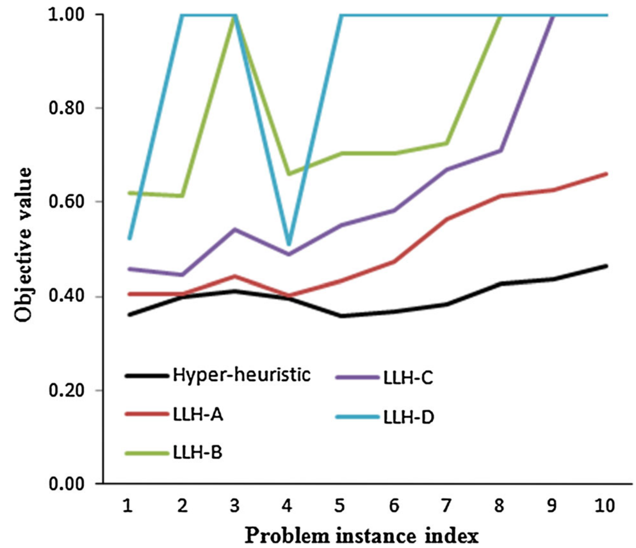


Fig. 8 Objective values obtained by the hyper-heuristic and the four individual LLHs

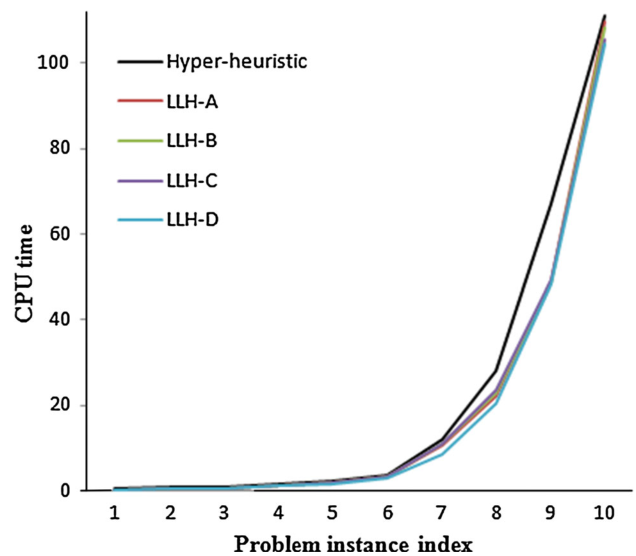


Fig. 9 CPU time consumed by the hyper-heuristic and the four individual LLHs

5 Conclusions

Engaging students in observing and learning from real-world targets has been recognized as being an important trend in educational settings. However, the constraints in real-world environments have seldom been discussed when conducing context-aware u-learning activities in most previous studies. In this paper, an optimization problem for determining personalized learning paths in the real world to maximize students' learning efficacy is formulated by taking the relevance between real-world learning targets and the environmental constraints into account. A hyper-heuristic algorithm is proposed to find quality solutions to the problem; moreover, a context-aware u-learning environment has been developed for an elementary school campus to evaluate the proposed approach. From the interviews of three experienced teachers, it has been found that the u-learning approach is able to motivate the students and improve their learning efficacy.

Although the application of the present study is related to the observation and identification of the plants on a school campus, the proposed approach can be applied to other in-field learning activities concerning real-world target observations, identification, and comparisons, for example, the ancient objects or artworks in temples or museums. It can also be applied to the observations of other natural objects, such as the features of rocks and terrains in different geographical locations and the plants in ecology parks. In addition, there are additional factors that can be considered in providing learning guidance in the future, such as the students' learning status and learning styles.

In the meantime, there are certain limitations to the approach. For example, while applying the u-learning approach to a new application, the location and available space of each real-world target, the corresponding QR-code tag, supplementary materials, and the learning task need to be defined and prepared. Moreover, the teachers need to provide the repertory content for determining the relevance of the learning targets. Therefore, to make this approach more applicable, it is worth developing effective tools to assist teachers in designing u-learning activities and preparing those needed materials.

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