

# Adaptive Learning Path Sequencing Based on Learning Styles within N-dimensional Spaces

Marc Normann

Faculty of Engineering  
University of Applied Science  
Aschaffenburg  
Aschaffenburg, Bavaria, Germany  
marc.normann@th-ab.de

Jim Haug

Faculty of Computer Science  
Kempten University of Applied  
Sciences  
Kempten, Bavaria, Germany  
jim.haug@hs-kempten.de

Yeimy Valencia

Faculty of Engineering  
University of Applied Science  
Aschaffenburg  
Aschaffenburg, Bavaria, Germany  
yeimy.valencia@th-ab.de.de

Jörg Abke

Faculty of Engineering  
University of Applied Science Aschaffenburg  
Aschaffenburg, Bavaria, Germany  
joerg.abke@th-ab.de

Georg Hagel

Faculty of Computer Science  
Kempten University of Applied Sciences  
Kempten, Bavaria, Germany  
georg.hagel@hs-kempten.de

## ABSTRACT

Planning adaptive learning paths for students' progress throughout a course can be a challenging task, although it can be helpful for their learning progress. Within the HASKI-System, students should be able to get their own, personalized learning paths. In this paper, we present an approach towards the learning path sequencing problem. This idea is based on a novel proposal for arranging learning objects in a multi-dimensional space, bringing the relationship and similarities of these objects into a new relationship. We show, that we can use both, the Ant Colony Optimization Algorithm and the Genetic Algorithm with the idea of the Traveling-Salesman-Problem and get results, that are comparable with a proposed literature-based adaption mechanism. Nevertheless, the learning paths are all personalized based on the Felder & Silverman Learning Style Model and the hyperspace model will allow us later on to include more dimensions for other influencing factors.

---

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from [Permissions@acm.org](mailto:Permissions@acm.org).

ECSEE 2023, June 19–21, 2023, Seeon/Bavaria, Germany  
© 2023 Copyright is held by the owner/author(s). Publication rights licensed to ACM.

ACM ISBN 978-1-4503-9956-2/23/06...\$15.00  
<https://doi.org/10.1145/3593663.3593676>

## CCS CONCEPTS

- Software and its engineering → Software creation and management.

## KEYWORDS

Learning Path Sequencing, Adaptive Learning Path, Ant Colony, Genetic Algorithm, Adaptive Learning Environment

## ACM Reference format:

Marc Normann, Jim Haug, Yeimy Valencia, Jörg Abke and Georg Hagel. 2023. Adaptive Learning Path Sequencing Based on Learning Styles within N-dimensional Spaces. In *ECSEE'23: European Conference of Software Engineering Education 2023, June 19-21, 2023, Seeon, Bavaria, Germany*, Jürgen Mottok and Georg Hagel (Eds.). ACM, New York, NY, USA, 10 pages. <https://doi.org/10.1145/3593663.3593676>

## 1 INTRODUCTION

In recent years, the field of Artificial Intelligence (AI) has witnessed impressive advancements. AI has the potential to further develop the education sector, particularly by expanding access to high-quality education to individuals globally and therefore promoting inclusivity and equitability in alignment with the United Nations' Sustainable Development Goals (SDGs) [36]. Adaptive Learning Environments (ALE) attempt to offer an alternative to non-individualized approaches by providing diverse services tailored to the learner's profile and characteristics. Adaptivity in this case is defined as modifying "a computer-assisted learning environment to students through runtime modeling" [34, p. 1]. The learning offer is

adapted to the individual differences of the learners. Lowendahl et al. [26, p. 7] describe adaptive learning as a procedure that "dynamically adjusts the way that instructional content is presented to students based on their comprehension of the material as revealed in their responses to embedded assessments or learner preferences such as visual presentation of materials". Studies have demonstrated that ALE can consider personalized factors such as a student's characteristics [19] and cognitive processes [40], offer customized feedback and interactions, and even create personalized curriculum and feedback [1, 25, 30, 31]. Previous research also indicates that in some areas, ALE have been very successful and equaled the tutoring of expert instructors [37].

The HASKI project (Hochschullehre: Adaptiv, selbstgesteuert und KI-gestützt) aims to develop an AI-supported recommendation system for university teaching that takes the preceding points into account. It is to be used in a blended learning environment and support learners with adaptive learning recommendations in their learning process.

The paper is structured as follows: In chapter 2 the current work on the topic is presented; In chapter 3 the idea of a 4-dimensional space based on Felder & Silverman Learning Style Model (FSLSM) is introduced and then in chapter 4 the idea of using Ant Colony Optimization (ACO) and Genetic Algorithm (GA). In the end, the results from testing are shown and the weaknesses of those models and what we can improve in the future are discussed.

## 2 RELATED WORK

Adaptive learning is a topic with lots of research in the last years. It is recognized as an emerging innovation especially in the context of higher education [4]. Following Hatties [21, p. 246] pledge for instructors as "adaptive learning experts" it can be argued that adaptive learning can achieve pedagogical benefits like e.g., acceleration, immediate feedback and interactive learning. ALE usually consist of three models: the learner model, the tutorial or instructional model and the domain or content model. While the learner model and the domain model fill the roles of representing the student and the content, the tutorial model resembles the algorithms that support the adaption of the instruction based on the data from the content and learner model. It sets the rules to what, when and how adaption can happen [28]. The literature shows that there can be several targets in ALE. Some examples are adaptive content, adaptive feedback, adaptive question difficulty and adaptive learning path [28]. While the overarching goal of the HASKI-System is to implement more than one of the aforementioned targets, the focus of this paper is on generating adaptive learning paths. The challenge that arises in this context is mainly known under the terms of Learning Path Sequencing Problem or Learning Path Adaptation Problem, but also Curriculum Sequencing. In this

paper, the first term is used. There are two main options to decide on how to tackle the Learning Path Sequencing Problem: On the one hand it can be based on statistical methods, neural networks and concept maps, on the other hand evolutionary algorithms and swarm intelligence is used [9]. The basis for the later one is often to see it as a Traveling-Salesman-Problem (TSP), which requires to consider an optimization problem. El Lakkah et al. [10] used the ACO and FSLSM [12] to determine the best fitting learning elements for a student. Based on a defined user and domain ontology, the proposed algorithm tries to fulfil the users learning goal. Yang et al. [41] proposed an improved ACO, the NACO, to solve the learning path sequencing problem and not getting stuck in a local optimum. It is based on a game-based approach for ACO and consists of an Ant Colony System (ACS) and a Max-Min Ant System (MMAS). El-Sabagh [11] developed an adaptive learning path based on the VARK learning style model. In their study, they showed, that this adaptivity can help students in higher education to get easier to their set learning goal. Menai et al. [29] tried to model a learning path according to the student's profile. It is viewed as a constraint satisfaction problem and based on Swarm Intelligence and ACO. It takes in the curriculum design constraints, time and difficulty constraints and tries to cover the objectives of a learner. The algorithm shows promising results. Fuchs et al. [15] introduced the idea of a Hypercube within their INTUITEL project to place a reproduction of students as vectors within a multidimensional space. These vectors represent the knowledge and the done Knowledge Objects for a student and the student should be recommended to stay close to a predefined learning path.

To the best of our knowledge, none of the existing approaches are tackling the learning path sequencing problem with a multidimensional space, that will place learning elements within it and at the same time allow to add or to substitute other known factors for the learning success apart from the learning style (LS). In the following chapter, the pedagogical background of the idea of the multidimensional space is introduced.

## 3 PEDAGOGICAL CONCEPT AND ONTOLOGY

### 3.1 Felder & Silverman Learning Style Model

Although the use of LS as a basis for educational practice in the context of an ALE is evidently popular [33], it has to be acknowledged that the concept has its flaws and issues. There are critics which highly question or deny the impact of LS in regards to enhancing learning because of lacking empirical evidence and contradicting results [3, 6, 32]. While these problems definitely should not be disregarded there are on the other side supporting studies that claim a positive influence on the learning process and its surrounding conditions if LS are taken into account in the context of an ALE [2, 22, 38]. Therefore, the LS concept has potential. HASKI will try to

compensate for its weaknesses by using the FSLSM [12] and its connected questionnaire the Index of Learning Styles (ILS) [13] which shows tendencies of students and does not deliver strict classifications as a theoretical basis. According to the FSLSM, every learner retains a preference across the four dimensions: active (ACT) or reflective (REF), sensing (SNS) or intuitive (INT), visual (VIS) or verbal (VER), and sequential (SEQ) or global (GLO). This approach, of using dimensions rather than types, allows for the depiction of a student's specific strengths in their preferred LS. It is the most applied LS model in the context of e-learning and is considered the most fitting model for implementing adaptive learning by some authors [23, 24, 39]. The aforementioned studies all based their adaptive mechanisms on the FSLSM. The reliability and validity of the ILS has also been thoroughly tested and been found adequate [14]. The ILS includes 44 items and detects LS on a spectrum in the aforementioned four dimensions. The items separate into 11 dichotomous forced-choice items, (a) and (b) for each of the four model dimensions. While (a) is the answer connected to the first dimension pole, (b) is associated with the second dimension pole. The selected alternatives are summed up cumulative: (a) adds +1 and (b) subtracts -1 from the score achieved in the affected dimension which is used to calculate an individual's learning preference. The resulting score can therefore vary between -11 and +11 [14].

### 3.2 The Adaption Mechanism

The framework of this mechanism for creating adaptive courses is based on the FSLSM and the work of Graf et al [17, 18]. The goal of the adaptive mechanism is to be flexible and provide a diverse range of 12 different learning objects (LOs) during the adaptation process. This aims to enhance the learner's learning experience by recommending the most suitable course structure and LOs that align with their LS using the adaptive link annotation and link sorting techniques. The various LOs are listed in Table 1. Graf et al. [17] assume a course structure that is separated into different sections where each section can but does not have to include the aforementioned 12 LOs. The authors formulate the existence of at least one Content Object (CO) in every section as the only working requirement of the mechanism. While their mechanism differentiates between an "Area before content" and an "Area after content", in HASKI this was modified to only show the other LOs after both the Commentary (CT) and CO were already recommended. The reason for this is to make sure every student worked on the CO and therefore the bulk of the exam relevant material without risking that the students lose interest or motivation beforehand and miss the most essential information. The remarks of the authors regarding the positive or negative influence of certain LOs depending on the individuals LS are the fundamental basis for the slightly adapted and interpreted mechanism in the context of HASKI.

**Table 1: Different LOs following Graf et al. [17, p. 32]**

Commentary (CT)	Brief overview
Content Object (CO)	Presents learning material
Reflection Quiz (RQ)	Open-ended questions to encourage reflection
Self-Assessment-Tests (SE)	Close-ended questions to check knowledge
Discussion Forum Activities (FO)	Ask questions and discuss topics with peers/ instructor
Additional Reading Material (RM)	Additional sources for reading, e.g., detailed explanations
Animations (AN)	Demonstrated concepts in an animated multimedia format
Exercises (EC)	Opportunity to practice learned knowledge
Examples (EX)	Presents theoretical content more concretely
Real-Life Applications (RA)	Demonstrates real-life utilization of the learning material
Conclusion (CC)	Summarizes learned content
Assignment (AS)	Describes the tasks necessary for assessing the course

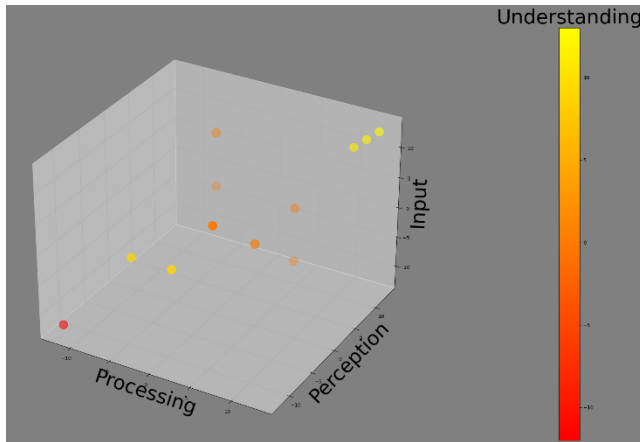
## 4 N-DIMENSIONAL SPACE FOR LEARNING OBJECTS

The approach for the adaptive learning paths within the HASKI-System is based on a multidimensional space, where each LO is assigned a specific coordinate. Those coordinates are based on the adaption mechanism by Graf et al. [17], which allocates each LS based on FSLSM a positive, a negative or a neutral influence on the LO. For the calculation of the coordinates, we transform those influences into 1 (positive), 0 (neutral) or -1 (negative) and multiply them by the value for the FSLSM dimension. Therefore, we use the following equation for the calculation:

$$X_k = dim_{ensoni} \times influence_j \quad (1)$$

Where k is the number of the coordinate (1=X, 2=Y, 3=Z, ...), i is the FSLSM dimension and j is the influence of the LS on the LO based on Graf et al. [17].

Since not all LO are rearranged in an adaptive way, it is needed to handle those exceptions and set default coordinates for them. Within the HASKI scope, the LO from the classification CT and CO are always at the beginning of the learning path, while the LO AS will always be at the end. Since the FSLSM dimensions can adopt values between 11 and -11, the values for those exceptions are greater or smaller. To ensure the cor-



**Figure 1: Example distribution of Learning Elements within a 4D-Space. Legend on the right shows 4th dimension**

rect positioning, the CT object gets 13 for all dimensions, the CO object 12 and the ZF object -12 in each coordinate.

With the creation of those coordinates, we can also place them within an N-dimensional space. As long as only the FSLSM is used, it will be a 4-dimensional space. Figure 1 represents an example distribution of LOs within this space and a possible visualization. To describe a fourth dimension, the color bar on the right is used. The elements in the top right corner represent the CT, CO and CC object, while the point in the lower left corner is the AS object. All other LOs are arranged in between.

## 5 LEARNING PATH SEQUENCING

To create personalized and adaptive learning paths, the system will use the coordinates from section 4. Therefore, the learning path sequencing problem will be considered as a Traveling Salesman Problem (TSP) and the path costs are set as the main parameter to optimize. Since it is not trivial to get the best solution for the TSP, meta-heuristics are used. Based on literature reviews, the most commonly used and promising algorithms are ACO and GA [27, 33]. Therefore, those algorithms are examined and compared in this paper.

### 5.1 Ant Colony Optimization

The ACO is inspired by the natural behavior of ants and belongs to the class of metaheuristic [7, 8]. Artificial ants will start from a point and visit new points by a random factor. The next point should be close to the current position, but does not need to be the closest in general. Each point will be visited exactly once and after the last point, the ants will return to their starting point. While traveling a path, the ants will leave evaporating pheromones, which will indicate the best results and turn the random factor of path finding into a more precise operation. The more ants follow a specific path, the higher the pheromones and the more ants will use this path as well. If a path is not used by other ants, the pheromones will slowly

disappear. The algorithm is typically used for solving the TSP and finding the shortest path in it [16, 35].

### 5.2 Genetic Algorithm

The GA belongs to the group of evolutionary algorithms and is modeled on nature [20]. The algorithm simulates the process of natural selection, i.e., those individuals that can adapt to changes in their environment survive, reproduce and pass on to the next generation of the evolutionary process. This iterative and optimization method has a set of individuals from a population of candidate solutions and, during each iteration, each individual is evaluated according to a previously defined criterion or fitness function. With this function it is decided which individuals are the fittest to survive and adapt and pass to the next generation, and which are the least fit, which are discarded and eliminated. This method is widely used to generate high quality solutions to optimization and search problems, such as the TSP.

The algorithm works as follows: at each iteration, a fitness score is evaluated for each individual, which is calculated using the fitness function. Those individuals with a fitness score will be subjected to variation using genetic re-combination operators called selection, crossover and mutation [5]. In the selection phase, after knowing the fitness of each individual, those that will be crossed and modified in the next generation will be selected. For this purpose, the individuals with the best aptitude will be taken into account, since they have a greater probability of being selected to form the population of the next generation. Crossover is the most important phase of a GA. For each pair of parents in the population, the genetic information of both parents is combined and a new offspring is generated. To perform the crossover, a crossover point within the genetic information of the parents is chosen at random and only parts of its internal representation are exchanged. In the mutation phase, some of the individual's genes may undergo mutations with a random probability. This means that part of the internal information of the individual is randomly modified, e.g., the bits of the individual. Once the genetic operators have been applied, the best individuals are selected to form the population of the next generation.

### 5.3 Learning Path Sequencing within HASKI

For the learning path sequencing problem within HASKI, the algorithms were used in basic versions without modifications. Both algorithms use the Euclidean Distance as the metric to find the optimal learning path.

Based on pedagogical concepts, that the CT and CO object are important for every student, it was decided, that those need to be the first two LO. The AS should be a way of summary and therefore be the last element. All other LO will be placed adaptively according to the LS of the student within the learning path.

## 6 TESTING

To test the approach and validate the idea of using an N-dimensional space, the two algorithms are compared with the adaption mechanism of Graf et al. [17], on which the idea is based. The expected result and therefore the hypothesis is that the results of the ACO and the GA are quite similar with Graf et al. [17] and the order of the learning elements are comparable.

### 6.1 Experimental Setup

The setup for the validation was based on six different LS, which have been randomly chosen from students from the Kempten University of Applied Science answering the ILS questionnaire.

The adapted mechanism for HASKI by Graf et al. [17] proposed the following learning paths for the LS presented in Table 2:

1. CT-CO-CC-EC-#AN-#SE-RQ-RA-#RM-#EX-FO-AS
2. CT-CO-AN-EX-RA-#SE-#EC-RQ-CC-FO-RM-AS
3. CT-CO-CC-AN-#SE-#EC-#RA-EX-FO-RQ-RM-AS
4. CT-CO-CC-EX-RA-AN-#SE-#EC-RQ-FO-RM-AS
5. CT-CO-CC-AN-#SE-#EC-RA-EX-FO-RQ-RM-AS
6. CT-CO-CC-AN-#SE-#EC-#RA-EX-RQ-FO-RM-AS

The sequence of learning elements with a hashtag (#) would be dependent on the didactic learning path. Those are the baseline learning paths for the comparison.

The proposed algorithms, the ACO and the GA, are tested with the same LS. They were tested independent from the HASKI-System itself as a Python script<sup>1</sup>. The scripts were executed on Windows 10 PCs with 16 GB RAM and 4 cores (Intel Core i5-7500) respectively 6 cores (AMD Ryzen 5 5500U) via the command line. No parallelization was performed in the code, but the learning paths for 2 different LS were run simultaneously on one computer.

Since the same result cannot be expected for each run because it is only a heuristic approximation and an NP-hard problem, the algorithms were tested a million times for each LS. Thus, a statistical statement can be made about how likely which learning paths are and what the distribution looks like.

### 6.2 Metrics

For the analysis of the test results, two metrics have been made to check the quality of the learning paths.

*Tolerance:* The tolerance describes the learning elements, which according to the calculation of Graf et al. [17] are very close to each other, but not equal. From a pedagogical point of view, these elements are interchangeable without distorting the learning path. A tolerance of +/-1 means that the learning

elements show a difference of 1 according to the calculation of Graf et al. [17].

*Deviation:* The deviation describes the LO which are still not in a valid position even after deducting the tolerance. If a deviation of +/-1 is assumed, it is examined in all valid learning paths with tolerance whether the LO is on a position before or after in the found learning path and thus a small deviation is present.

In addition to the metrics of tolerance and deviation, the number of different learning paths, the path costs and the calculation time was measured for the algorithms. Therefore, for time and costs the minimum, the maximum, the average and the median values were calculated as well as the deviation and the variance. Hence, statistical statements can be made on the data.

The main focus is put on the metrics *tolerance* and *deviation*. Here, it is expected that the results will get as close as possible to Graf et al. [17] and therefore reach a score off at least 85% to be validated as good. Nevertheless, it is to be expected, that there may be bigger aberrations in the learning paths. Thus, a score of more than 50% would still be seen as acceptable. If too many scores are below 50%, a further investigation might be needed to sort out the errors and check, if there is a connection with the learning styles, that were used.

The number of different learning paths should be as low as possible. A result of maximum 5 different LPs is seen as good, while more than 10 different LPs seem to be too problematic. The focus for the time measurement is based on the usage within the system. Here, a calculation time of about one second would be great while a calculation time of more than 3 seconds is considered as problematic.

### 6.3 Results

The results of the testing (see Table 2) show, that the idea of the N-dimensional space is working in general, even though, the results are not as close to the adaption mechanism by Graf et al. [17] as expected when granting a tolerance of +/-1 or +/-2. Only in one case, nearly 75% of the calculated learning paths from the ACO are exactly as the ones proposed by Graf et al. [17]. One other LS gets in 50% of the tests a learning path, that is within the tolerance level of +/- 2. However, if the deviation is taken into account, it becomes apparent that the ACO deviates only slightly from the comparison data and five out of six learning paths are within the metric.

Further investigation of the deviation was made to determine if there were specific learning items that fell outside the range of variance (three or more positions). However, it is unfortunately not possible to say here that one or two specific

<sup>1</sup> Used scripts for the analysis and data from the runs are available at <https://github.com/HASKI-RAK/paper/tree/main/AnalysisACOandGA>

LO cause an invalid learning path, since these differ depending on the LS and different ones contribute to the errors.

If comparing the ACO and the GA in terms of the learning path costs, both algorithms have very similar numbers and hardly differ from each other. Especially the lowest path costs are very similar to each other. This indicates, that the approximation works with both of the selected algorithms.

In terms of the calculation time, the ACO is better than the GA. With nearly one second, the GA takes up about 10 times as much calculation time as the ACO. Also, the standard deviation is always bigger by up to ten times. Nevertheless, both algorithms can calculate a learning path in an acceptable time and are therefore suitable for the HASKI-System.

A bigger difference can be recognized with the number of different learning paths created by the algorithms for the same LS. While the GA seems to produce a larger quantity of learning paths, the produced different learning paths for the ACO are often diverse too and could lead to problems during the usage in the HASKI-System. Especially the first tested LS seems to make problems in the ACO with 12 different paths.

Since the metrics introduced in section 6.2 and the postulated results are not met in every case (especially with the GA), it was decided to do a further testing with different LS. The six LS tested also show a tendency toward a global and sensing learning style, wherefore a more balanced selection of LS should be considered and possibly can indicate more

**Table 2: Results of the experiment made with the ACO (first number) and GA (second number) with one million runs each. Bold-italic numbers indicate a very good, underlined numbers show a good result according to section 6.2.**

Learning Style	ACT: 5, INT: 9, VIS: 9, GLO: 9	REF: 1, SNS: 7, VIS: 5, SEQ: 5	ACT: 3, SNS: 7, VIS: 3, GLO: 3	REF: 3, SNS: 7, VIS: 5, GLO: 5	ACT: 5, SNS: 7, VIS: 7, GLO: 3	ACT: 1, SNS: 7, VIS: 5, GLO: 1
Nr of LPs	12 77	<u>8</u> 49	<b>2</b> 19	<b>4</b> <u>10</u>	<b>2</b> 34	<b>4</b> <b>2</b>
Tolerance +/- 0	0% 0%	11,73% 0%	0% 0%	0% 0%	0% 0%	<u>74,99%</u> 0%
Tolerance +/- 1	0% 0%	11,73% 0%	0% 0%	0% 0%	0% 0%	<b>100%</b> 0%
Tolerance +/- 2	0% 0%	<u>50,69%</u> 0%	0% 0%	0% 0%	0% 0%	<b>100%</b> 0%
Deviation +/- 1	0% 0%	<b>100%</b> 0%	<b>100%</b> 0%	<b>93,78%</b> 0%	0% 0%	<b>100%</b> 0%
Deviation +/- 2	0% 0%	<b>100%</b> 0%	<b>100%</b> 0%	<b>100%</b> 0%	<b>100%</b> 0%	<b>100%</b> 0%
Costs Min	124,81 124,81	68,72 68,72	72,26 72,26	81,14 81,14	89,84 83,2	66,09 66,09
Costs Avg	129,20 125,36	69,03 68,72	72,26 73,30	81,18 82,69	89,84 85,68	66,26 66,09
Costs Median	128,63 124,81	69,08 68,72	72,26 72,26	81,14 81,98	89,84 84,24	66,09 66,09
Costs Max	135,16 140,87	69,47 79,30	72,26 79,18	81,79 85,71	89,84 94,59	66,77 66,09
Costs Deviation	3,87 1,29	0,28 0,16	0 1,67	0,16 1,50	0 2,55	0,30 0
Costs Variance	15,01 1,66	0,08 0,02	0 2,79	0,02 2,26	0 6,52	0,09 0
Time Min (sec)	0,04 0,86	0,04 0,87	0,04 0,86	0,04 0,86	0,04 0,84	0,03 0,86
Time Avg (sec)	<b>0,06</b> <b>0,94</b>	<b>0,05</b> <b>0,93</b>	<b>0,05</b> <b>0,91</b>	<b>0,06</b> <b>0,91</b>	<b>0,06</b> <b>0,89</b>	<b>0,05</b> <b>0,91</b>
Time Median (sec)	<b>0,06</b> <b>0,94</b>	<b>0,05</b> <b>0,94</b>	<b>0,05</b> <b>0,91</b>	<b>0,05</b> <b>0,91</b>	<b>0,05</b> <b>0,89</b>	<b>0,05</b> <b>0,91</b>
Time Max (sec)	1,65 1,56	0,81 1,59	0,81 1,61	0,84 1,66	0,84 1,97	0,82 2,12
Time Deviation (sec)	0,007 0,014	0,006 0,025	0,006 0,013	0,010 0,019	0,009 0,013	0,009 0,032
Time Variance (ms)	0,05 0,20	0,03 0,62	0,03 0,16	0,11 0,35	0,09 0,17	0,09 1,00

interesting insights. The results will be presented in the next section.

### 6.4 Anomaly investigations

To further investigate the anomalies found, 25 new LS were generated randomly and each one was tested 25.000 times on each algorithm (see Table 3).

Since the metrics of the path costs and the calculation time are not very different from the ones shown in Table 2 and in terms of clarity, it was decided to only show the number of generated LPs as well as the accuracy with tolerance and deviation granted. The complete data from the testing are accessible via GitHub<sup>2</sup>.

The results of the second tests with 25 more LS show very similar results to the first results. Here, the matches with Graf et al. [17] and tolerance are not good too. Only two LS show a 100% match when calculated with ACO and tolerance granted, 18 LS show no match at all. Regarding the GA, out of the 25 LS, no learning path does match with the comparison learning paths. However, when regarding the deviation, it seems again, that the N-dimensional space is working in general, but not with the exact same learning paths. 13 out of 25 learning paths calculated with ACO show a minimum match of 50%, eight of them have a match of more than 85%.

Here as well, a closer look at the errors do not provide clear evidence for specific LO, which are mainly responsible for non-

**Table 3: Results of the experiment made with the ACO (first number) and GA (second number) with 25.000 runs each. Bold-italic numbers indicate a very good, underlined numbers show a good result according to section 6.2.**

Learning Style	Nr of LPs	Tolerance +/- 0	Tolerance +/- 1	Tolerance +/- 2	Deviation +/- 1	Deviation +/- 2
ACT: 7, INT: 11, VRB: 9, GLO: 3	23 26	0% 0%	0% 0%	0% 0%	0,82% 0%	<u>50,06%</u> 0%
REF: 7, INT: 11, VRB: 7, GLO: 7	<b>2</b> 31	0% 0%	0% 0%	0% 0%	0% 0%	0% 0%
REF: 9, INT: 3, VIS: 1, GLO: 3	<b>2</b> <b>2</b>	0% 0%	0% 0%	0% 0%	0% 0%	0% 0%
REF: 11, INT: 9, VIS: 1, GLO: 5	<b>2</b> 30	0% 0%	0% 0%	0% 0%	0% 0%	0% 0,20%
REF: 1, INT: 3, VIS: 3, GLO: 1	19 11	4,18% 0%	15,04% 0%	15,04% 0%	49,30% 41,51%	49,30% <b>99,20%</b>
ACT: 7, INT: 5, VIS: 3, SEQ: 1	<b>4</b> <u>9</u>	0% 0%	0% 0%	0% 0%	0% 0%	<u>54,96%</u> 0%
ACT: 5, INT: 7, VRB: 11, SEQ: 7	19 28	0% 0%	0% 0%	0% 0%	0% 0%	16,75% 0,64%
ACT: 3, SNS: 7, VIS: 7, GLO: 9	<u>8</u> 13	0% 0%	0% 0%	0% 0%	0% 0%	<u>68,69%</u> 0%
ACT: 11, SNS: 7, VIS: 1, GLO: 11	<b>2</b> <b>4</b>	0% 0%	0% 0%	0% 0%	0% 0%	<b>100%</b> 0%
ACT: 3, INT: 5, VIS: 11, SEQ: 1	<u>8</u> 37	0% 0%	0% 0%	0% 0%	0% 0%	0% 0%
ACT: 9, INT: 5, VRB: 11, SEQ: 3	<b>4</b> 46	0% 0%	0% 0%	0% 0%	0% 0%	0,58% 0%
ACT: 1, SNS: 3, VIS: 11, GLO: 5	20 <u>8</u>	10,18% 0%	20,72% 0%	20,72% 0%	40,23% 0%	48,14% 0%
ACT: 1, SNS: 9, VRB: 7, SEQ: 5	<b>2</b> 67	0% 0%	0% 0%	0% 0%	0% 0%	<b>100%</b> 0%
REF: 1, SNS: 1, VIS: 11, SEQ: 5	144 <u>8</u>	0,84% 0%	4,81% 0%	12,81% 0%	43,36% 0%	<u>63,28%</u> 0%
ACT: 7, INT: 11, VRB: 7, SEQ: 11	19 <b>4</b>	0% 0%	0% 0%	0% 0%	2,76% 0%	<b>85,80%</b> 1,44%

<sup>2</sup> <https://github.com/HASKI-RAK/paper/tree/main/AnalysisACOandGA>

valid learning paths. For the path costs and the calculation time, the calculation for 25 more learning paths did not provide new insights.

In general, it shows that in large parts at least the differences between the ACO and Graf et al. [17] remain manageable. Those learning paths need to be tested more and with students evaluating them, to make a clear statement on the quality. In contrast, the GA shows that even with further LS the matches with the comparison algorithm are not given.

Only in two cases and with a deviation of 2 a good comparison with Graf et al. [17] can be drawn. In all other cases, no or only a few LPs emerged that are similar to the comparison mechanism.

As before, the number of suggested learning paths varies considerably here and increases drastically in places. However, some of the generated learning paths still fall within the tolerance or are at least compensated for by the deviation.

A statement about whether a certain LS dimension is possibly responsible for this is not possible. There are no indications for this. When looking at the learning path costs and the processing time, no further peculiarities to the first test stand out. The data seem to confirm the results here.

## 7 CONCLUSION AND FURTHER RESEARCH

In this paper, a new approach for calculating adaptive learning paths is presented. It is built upon an N-dimensional space and is considered as an optimization problem. Two algorithms, the Ant Colony Optimization and the Genetic Algorithm, were used and compared. The learning paths generated by the adaptation mechanism according to Graf et al. [17] were used for this comparison.

In total, the exact matches between the algorithms are not very good, but with a granted tolerance, which is related to the pedagogical properties of the LO, the results look better and show a general working of the approach. The investigation of the errors shows, that mostly one or two LO are placed wrong to make the learning path not match with the comparative result. For the ACO, 20% of the LPs calculated had no error at all, 16% one, 20% two and 44% three or more errors. For the GA, only in 8% of the LPs, there is one error, otherwise all LPs had at least three erroneous LO. Unfortunately, those LO are individual for each learning path and it cannot be narrowed down to one or two. Thus, the model still has some limitations, which need to be considered when using this approach.

We optimized our algorithmic approaches in this paper towards being as similar as possible to the results of the HASKI-modified adaption mechanism by Graf et al. [17], which was

**Table 3 (Continuation): Results of the experiment made with the ACO (first number) and GA (second number) with 25.000 runs each. Bold-italic numbers indicate a very good, underlined numbers show a good result according to section 6.2.**

Learning Style	Nr of LPs	Tolerance +/- 0	Tolerance +/- 1	Tolerance +/- 2	Deviation +/- 1	Deviation +/- 2
REF: 7, INT: 9, VIS: 7, SEQ: 9	24 22	0% 0%	0% 0%	0% 0%	0% 0%	<b><i>97,14%</i></b> <u>65,00%</u>
REF: 1, INT: 9, VRB: 5, GLO: 9	16 2	0% 0%	0% 0%	0% 0%	0% 0%	49,94% 0%
ACT: 9, SNS: 1, VRB: 11, GLO: 9	2 59	0% 0%	0% 0%	0% 0%	<b><i>100%</i></b> 0%	<b><i>100%</i></b> 0%
REF: 9, SNS: 5, VIS: 1, GLO: 11	<u>8</u> 44	0% 0%	0% 0%	0% 0%	0% 0%	0% 0%
REF: 1, INT: 9, VIS: 9, SEQ: 5	54 <u>8</u>	12,92% 0%	36,83% 0%	36,83% 0%	<u>51,57%</u> 0%	<u>51,78%</u> 0%
ACT: 1, INT: 9, VRB: 9, SEQ: 9	11 2	11,96% 0%	23,13% 0%	49,95% 0%	49,95% 0%	49,95% 0%
REF: 7, SNS: 3, VRB: 9, GLO: 7	<u>8</u> 34	0% 0%	0% 0%	0% 0%	0% 0%	<b><i>90,56%</i></b> 0%
ACT: 9, SNS: 3, VIS: 5, SEQ: 1	2 4	<b><i>100%</i></b> 0%	<b><i>100%</i></b> 0%	<b><i>100%</i></b> 0%	<b><i>100%</i></b> 0%	<b><i>100%</i></b> 0%
ACT: 1, SNS: 5, VIS: 7, SEQ: 1	4 2	<u>72,62%</u> 0%	<u>72,62%</u> 0%	<b><i>100%</i></b> 0%	<b><i>100%</i></b> 0%	<b><i>100%</i></b> 0,20%
ACT: 3, SNS: 9, VRB: 11, SEQ: 9	3 82	0% 0%	0% 0%	0% 0%	0% 0%	0% 0%



evaluated and validated but is obviously not the only way to generate learning paths on the basis of LS, e.g. [2] and [10] are using different proposals. From a strict pedagogical point of view a learning path being different compared to the aforementioned mechanism is therefore no clear exception criterion for practical use. It does not make it adequate or inadequate in a general sense since there is no gold standard. Learning paths are always individual and the focus on the LS alone probably offers too few clues to allow more precise analyses of which success factors make up a learning path. For this reason, the proposed technique will be improved in the future. Here, additional dimensions should be included and replace LS over time, as soon as more data about students is available. Important points here are especially the knowledge level of a student and their learning analytics data. The theorem of the Zone of Proximal Development seems to have potential as the basis for the multidimensional cube with different learner characteristics.

There is also room for improvement in the models themselves. For example, focusing solely on learning pathway costs can be a hindrance and more optimization criteria should be included. Improvements can also be targeted through the use of more recent variations of the algorithms.

However, the final evaluation of the learning paths is up to the students. An initial test phase and a survey of them is planned in the near future in order to obtain feedback on which influences need to be taken into account. Subsequently, the appropriate adjusting screws can be examined and improved.

## ACKNOWLEDGMENTS

This work was supported by the German Federal Ministry of Education and Research (BMBF), grant number 16DHBK1036, and the Bavarian State Ministry of Science and Art. The responsibility for the content of this publication remains with the authors.

## REFERENCES

- [1] Fatema AlShaikh and Nabil Hewahi. 2021. AI and Machine Learning Techniques in the Development of Intelligent Tutoring System: A Review. In *Proceedings of the 2021 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT)*, September 29-30, 2021, Bahrain. 403-410. DOI: 10.1109/3ICT53449.2021.9582029.
- [2] Mohammad Alshammari and Amjad Qtaish. 2019. Effective Adaptive E-Learning Systems According to Learning Style and Knowledge Level. *Journal of Information Technology Education: Research* 18, 529-547. DOI:10.28945/4459.
- [3] Donggun An and Martha Carr. 2017. Learning styles theory fails to explain learning and achievement: Recommendations for alternative approaches. *Personality and Individual Differences*, 116 (Oct. 2017), 410-416. DOI: 10.1016/j.paid.2017.04.050.
- [4] Samantha A. Becker, Malcolm Brown, Eden Dahlstrom, Annie Davis, Kristi DePaul, Veronica Diaz, and Jeffrey Pomerantz. 2018. Horizon Report: 2018 Education Edition. Retrieved February 27, 2023 from <https://library.educause.edu/~media/files/library/2018/8/2018horizonreport.pdf>.
- [5] Cunling Bian, Shijun Dong, Chunrong Li, Zheng Shi, and Weigang Lu. 2017. Generation of adaptive learning path based on concept map and immune algorithm. In *Proceedings of the 12th International Conference on Computer Science and Education (ICCSE)*, August 22 - 25, 2017, Houston, TX, USA. 409-414. DOI: 10.1109/ICCSE.2017.8085526.
- [6] Joshua Cuevas. 2015. Is learning styles-based instruction effective? A comprehensive analysis of recent research on learning styles. *Theory and Research in Education* 13, 3 (2015), 308-333. DOI:10.1177/1477878515606621.
- [7] Marco Dorigo, Mauro Birattari, and Thomas Stützle. 2006. Ant colony optimization. *IEEE Computational Intelligence Magazine* 1, 4 (Nov. 2006), 28-39. DOI: 10.1109/MCI.2006.329691.
- [8] Marco Dorigo and Thomas Stützle. 2019. Ant Colony Optimization: Overview and Recent Advances. *Handbook of Metaheuristics (3rd ed.)*. International Series in Operations Research & Management Science, Vol. 272. Springer, Cham. DOI: 10.1007/978-3-319-91086-4\_10.
- [9] Pragma Dwivedi, Vibhor Kant, and Kamal K. Bharadwaj. 2017. Learning path recommendation based on modified variable length genetic algorithm. *Education and Information Technologies* 23 (Aug. 2017), 819-136. DOI: 10.1007/s10639-017-9637-7.
- [10] Sabrine El Lakkah, Mohammed A. Alimam, and Hamid Seghioeur. 2017. Adaptive e-learning system based on learning style and ant colony optimization. In *Proceedings of the 2017 Intelligent Systems and Computer Vision (ISCV)*, April 17 - 19, 2017, Fez, Morocco. 819-836. DOI: 10.1109/ISCV.2017.8054963.
- [11] Hassan A. El-Sabagh. 2021. Adaptive e-learning environment based on learning styles and its impact on development students' engagement. *International Journal of Educational Technology in Higher Education* 18, 53 (Oct. 2021). DOI: 10.1186/s41239-021-00289-4.
- [12] Richard M. Felder and Linda Silverman. 1988. Learning and Teaching Styles in Engineering Education. *Journal of Engineering Education* 78, 7 (1988), 674-681.
- [13] Richard M. Felder and Barbara A. Soloman. 1996. Index of Learning Styles Questionnaire. NC State University. Retrieved February 27, 2023 from <https://www.webtools.ncsu.edu/learningstyles/>.
- [14] Richard M. Felder and Joni Spurlin. 2005. Applications, reliability and validity of the Index of Learning Styles. *International Journal of Continuing Engineering Education* 21, 103-122.
- [15] Kevin Fuchs, Peter A. Henning, and Mutfried Hartmann. 2016. INTUITEL and the Hypercube Model - Developing Adaptive Learning Environments. *Journal of Systemics, Cybernetics and Informatics*, 14, 3 (Jun 2016), 7-11.
- [16] Rongwei Gan, Qingshun Guo, Huiyou Chang, and Yang Yi. 2010. Improved ant colony optimization algorithm for the traveling salesman problems. *Journal of Systems Engineering and Electronics* 21, 2 (Apr. 2010), 329-333. DOI: 10.3969/j.issn.1004-4132.2010.02.025.
- [17] Sabine Graf, Kinshuk, and Cindy Ives. 2010. A Flexible Mechanism for Providing Adaptivity Based on Learning Styles in Learning Management Systems. In *Proceedings of the 10th IEEE International Conference on Advanced Learning Technologies (ICALT 2010)*, July 5 - 7, 2010, Sousse, Tunisia. 30-34. DOI: 10.1109/ICALT.2010.16.
- [18] Sabine Graf, Ting-Wen Chang, Anne Kersebaum, Thomas Rath, and Jeffrey Kurcz. 2014. Investigating the Effectiveness of an Advanced Adaptive Mechanism for Considering Learning Styles in Learning Management Systems. In *Proceedings of the 14th International Conference on Advanced Learning Technologies (ICALT)*, July 7 - 10, 2014, Athens, Greece. 112-116. DOI: 10.1109/icalt.2014.41.
- [19] Arthur C. Graesser, Zhiqiang Cai, Brent Morgan, and Lijia Wang. 2017. Assessment with computer agents that engage in conversational dialogues and dialogues with learners. *Computers in Human Behavior* 76 (Nov. 2017), 607-616. DOI: 10.1016/j.chb.2017.03.041.
- [20] John J. Grefenstette. 1986. Optimization of Control Parameters for Genetic Algorithms. *IEEE Transactions on Systems, Man, and Cybernetics* 16, 1 (Jan. 1986), 122-128. DOI: 10.1109/TSMC.1986.289288.
- [21] John Hattie. 2008. Visible learning: A synthesis of over 800 meta-analyses relating to achievement (1st ed.). Routledge, London, UK.
- [22] Ioannis Karagiannis and Maya Satratzemi. 2018. Implementation of an Adaptive Mechanism in Moodle Based on a Hybrid Dynamic User Model. In *Proceedings of the 21st International Conference on Interactive Collaborative Learning (ICL2018)*, September 25-28, 2018, Kos Island, Greece. 377-388. DOI: 10.1007/978-3-030-11932-4\_36.
- [23] Iraklis Katsaris and Nikolas Vidakis. 2021. Adaptive e-learning systems through learning styles: A review of the literature. *Advances in Mobile Learning Educational Research* 1, 2 (2021), 124-145. DOI: 10.25082/amler.2021.02.007.
- [24] Jasna Kuljis and Fang Liu. 2005. A Comparison of Learning Style Theories on the Suitability for elearning. *Web Technologies, Applications, and Services* (Jul. 2005), 191-197.

- [25] Chun F. Lin, Yu-chu Yeh, Yu H. Hung, and Ray I Chang. 2013. Data mining for providing a personalized learning path in creativity: An application of decision trees. *Computers & Education*, 68 (Oct. 2013), 199-210. DOI: 10.1016/j.compedu.2013.05.009.
- [26] Jan-Martin Lowendahl, Terri-Lynn B. Thayer, and Glenda Morgan. 2016. Top 10 strategic technologies impacting higher education in 2016. *Gartner Research Note G00294732*, 15.
- [27] Marcelo de Oliveira Costa Machado, Natalie Ferraz Silva Bravo, André Ferreira Martins, Heder Soares Bernardino, Eduardo Barrere and Jairo Francisco de Souza. 2021. Metaheuristic-Based Adaptive Curriculum Sequencing Approaches: A Systematic Review and Mapping of the Literature. In *Artificial Intelligence Review*, 54 (2021), 711-154. DOI: 10.1007/s10462-020-09864-z.
- [28] Florence Martin, Yan Chen, Robert L. Moore, and Carl D. Westine. 2020. Systematic review of adaptive learning research designs, context, strategies, and technologies from 2009 to 2018. *Educational Technology Research and Development* 68 (Jun. 2020), 1903-1929. DOI: 10.1007/s11423-020-09793-2.
- [29] Mohamed E. B. Menai, Hamad Alhunitah, and Hussein Al-Salman. 2018. Swarm intelligence to solve the curriculum sequencing problem. *Computer Applications in Engineering Education* 26, 5 (Aug. 2018), 1393–1404. DOI: 10.1002/cae.22046.
- [30] Anabil Munshi and Gautam Biswas. 2019. Personalization in OELs: Developing a Data-Driven Framework to Model and Scaffold SRL Processes. In *Proceedings of the International Conference on Artificial Intelligence in Education (AIED 2019)*, June 25-29, 2019, Chicago, IL, USA. 354-358. DOI: 10.1007/978-3-030-23207-8\_65.
- [31] Tong Mu, Shuhan Wang, Erik Andersen, and Emma Brunskill. 2018. Combining adaptivity with progression ordering for intelligent tutoring systems. In *Proceedings of the Fifth Annual ACM Conference on Learning at Scale (L@S '18)*, June 26 - 28, 2018, London, United Kingdom. ACM Inc., New York, NY, 1-4. DOI: 10.1145/3231644.3231672.
- [32] Harold Pashler, Mark McDaniel, Doug Rohrer, and Robert Bjork. 2008. Learning Styles: Concepts and Evidence. *Psychological Science in the Public Interest* 9, 3 (2008), 105–119. DOI: 10.1111/j.1539-6053.2009.01038.x.
- [33] Nisha S. Raj and V. G. Renumol. 2022. A systematic literature review on adaptive content recommenders in personalized learning environments from 2015 to 2020. *Journal of Computers in Education* 9, 1 (2022), 113-141. DOI: 10.1007/s40692-021-00199-4.
- [34] Werner Stangl. Adaptivität. Retrieved February 27, 2023 from <https://lexikon.stangl.eu/982/adaptivitaet>.
- [35] Petr Stodola, Pavel Otřisal, and Kamila Hasilová. 2022. Adaptive Ant Colony Optimization with node clustering applied to the Travelling Salesman Problem. *Swarm and Evolutionary Computation* 70 (Apr. 2022). DOI: 10.1016/j.swevo.2022.101056.
- [36] United Nations, Department of Economic and Social Affairs. 2022. Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all. Retrieved February 27, 2023 from <https://sdgs.un.org/goals/goal4>.
- [37] Kurt VanLehn. 2011. The Relative Effectiveness of Human Tutoring, Intelligent Tutoring Systems, and Other Tutoring Systems. *Educational Psychologist* 46, 4 (Oct. 2011), 197-221. DOI: 10.1080/00461520.2011.611369.
- [38] Ravindra Vaidya and Manish Joshi. 2017. Use of Learning Style Based Approach in Instructional Delivery. *Lecture Notes in Networks and Systems*, 199–209. DOI: 10.1007/978-981-10-6916-1\_18.
- [39] Ana L. Velázquez and Saïd Assar. 2007. Using learning styles to enhance an e-learning system. In *Proceedings of the Sixth European conference on e-learning (ECEL 2007)*, October 4 - 5, 2007, Copenhagen, Denmark.
- [40] Longkai Wu and Chee-Kit Looi. 2010. Agent Prompts: Scaffolding Students for Productive Reflection in an Intelligent Learning Environment. In *Proceedings of the 10th International Conference on Intelligent Tutoring Systems (ITS 2010)*, June 14-18, 2010, Pittsburgh, PA, USA. 426-428. DOI: 10.1007/978-3-642-13437-1\_92.
- [41] Kang Yang, Xiaoming You, Shen Liu, and Han Pan. 2020. A novel ant colony optimization based on game for traveling salesman problem. *Applied Intelligence* volume 50 (Jul. 2020), 4529-4542. DOI: 10.1007/s10489-020-01799-w.