Assessing conceptual mapping based active learning for advancing engineering diagnostic skills

Dr. Yuetong Lin, Indiana State University

Yuetong Lin received the Ph.D. degree in Systems and Industrial Engineering from the University of Arizona, Tucson, in 2005. He was with Indiana State University from 2005 to 2016, where he became associate professor of Electronics and Computer Engineering Technology, and the program coordinator for Computer Engineering Technology. He joined Embry-Riddle Aeronautical University, Worldwide in September 2016 as an associate professor in the Department of Engineering and Technology.

Dr. A. Mehran Shahhosseini, Indiana State University

A. Mehran Shahhosseini is an Associate Professor in the Department of Applied Engineering and Technology Management at Indiana State University. He has published over 45 articles in different journals and conference proceedings. He has served as an investigator for research projects sponsored by National Science Foundation, Ford Motor Company, and the US Army. Before working at Indiana State University, he was a faculty in the University of Louisville for 10 years. He also has over four years of industrial experience. He received his D.Eng. degree in Mechanical Engineering from Lamar University (USA) in 1999, M.Sc. in Materials Engineering from Isfahan University of Technology (Iran) in 1991, and B.Sc. in Metallurgical Engineering from Tehran University (Iran) in 1988. He is a member of ASEE, ASME, SAE, and ATMAE.

Dr. M. Affan Badar, University of Sharjah & Indiana State University

M. Affan Badar, PhD is Professor & Chair, Industrial Engineering & Eng Mgt Department at University of Sharjah (UAE). He is a tenured professor in Applied Engineering & Technology Management Department at Indiana State University (USA) where he also served as interim associate dean, dept chair, and program coordinator. He is an ABET program evaluator. He received a Ph.D. degree in Industrial Engineering from the University of Oklahoma, M.S. in Mechanical Engineering from King Fahd University of Petroleum and Minerals, and M.Sc. in Industrial Engineering and B.Sc. (Hons.) in Mechanical Engineering from Aligarh Muslim University. Dr. Badar has published more than 50 articles in refereed journals and proceedings in the areas of coordinate metrology, lean manufacturing, health care, energy system design

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Introduction

Active learning differs from traditional instructional pedagogy by emphasizing student activities and engagement in the learning process. The most frequently discussed types of active learning are collaborative learning, co-operative learning, and problem-based learning. Various studies, from using interactive, hands-on lessons and activities designed to teach research process to undergraduate engineering students[1], to preparing manufacturing engineering students through competitions, projects sponsored by industry, capstone projects, laboratory exercises or projects simulating real-life scenarios[2], have shown that active learning increases student performance in STEM subjects.

Critical thinking, identified by The U. S. Department of Labor as the raw material of a number of key workplace skills such as problem solving, decision making, organizational planning, and risk management, is highly coveted by employers of engineering graduates. It not only requires demonstration of solid domain knowledge, but also the application of knowledge in addressing real-world problems. According to Chartrand et al.[3], 69% of industry executives admit they assess critical thinking skills in the selection process. Similarly, a report commissioned by the Association of American Colleges and Universities (AAC&U) finds that more than 75% of employers want more focus on five key career preparation areas: critical thinking, complex problem-solving, written and oral communication, and applied knowledge in real-world settings[4]. Meanwhile, these studies indicate that 49% of employers rate their employees' critical thinking skills as only average or below average, and only 28% of employers rated four-year graduates as having "Excellent" critical thinking skill. Obviously, a more concerted effort must be made in curricula and educational practices to achieve a more measurable outcome to close the skill gap in fresh college graduates.

Active learning, with its strategy especially in the computer-based classroom[5], is ideal to blend pertinent curriculum elements to help students develop the highly-sought abilities. The issues now become: *a*) identifying the proper problem to provide context and motivation; and *b*) finding the technical vehicle for student engagement and assessment.

For the first issue, Kahlen et al.[6] and Benner et al.[7] show that providing accurate and timely diagnosis for system failures or malfunctions embodies the culmination of the aforementioned skills and is a common theme in many STEM in particular engineering and medical disciplines. And for the second issue where students' mastery of the skills is to be demonstrated and evaluated, we find concept maps to be fitting because of their use of both content and process knowledge to create visual maps of a diagnostic strategy to identify technical problems[8,9].

We have found the needed platform to assess concept map based active learning in a National Science Foundation funded project, "Advancing Diagnostic Skills Training in the Undergraduate Technology and Engineering Curriculum". On one hand, the project uses concept map to both solicit input from domain experts and assess student outcomes. On the other hand, the project deliverable helps novice troubleshooters (i.e., students) learn important principles about diagnostics and become competent in troubleshooting system malfunctions, a critical thinking and problem solving skill desired by employers. The self-paced, computer-based training engages students in a way that is consistent with active learning practice.

Two training modules have been fully developed and tested at five institutions and by about one hundred students in engineering technology programs. In this paper we present student feedback, both qualitative and quantitative, from these trials. The results represent preliminary assessment of concept map based approach in improving student critical thinking skills and more broadly, the effectiveness of active learning in increasing student performance in STEM.

The rest of the paper is organized as follows. We first briefly introduce concept mapping and its application in active learning. The assessment plan is then discussed, and the validation data is presented and analyzed. We conclude the paper with observations and direction for future work.

Concept Map based Learning

Conceptual mapping is a well-recognized approach that uses both content knowledge and process knowledge to prompt users to create visual maps of a diagnostic strategy to identify technical problems in complex technical systems[10]. A comprehensive study of applications of concept maps in higher education is provided by Pia et al.[11]. A few noteworthy examples are highlighted here. An interesting case is illustrated by Krupczak et al.[12],[13] where concept maps are used to communicate major aspects of technological systems to non-engineering students with limited background knowledge. Castles and Lohani[14] present an example of building a comprehensive concept map and an appropriate concept inventory to implement concept-inventory-driven analysis of student knowledge in a large freshman mechatronics course unit. A Diagnostic and Remedial learning system is introduced by Acharya and Sinha[15] to help pinpoint the exact concept where the student is deficient. An effective role of concept mapping in teaching, learning, and assessment in Power Electronics is described by Raud et al.[16]. Hwang et al.[17] show that a computerized collaborative concept-mapping approach both reduces the cognitive load, and improves learning achievements of the students. Triplett et al.[18] propose Concept-in-Context maps (CCmaps) to link a wide array of different types of information that reflect the organization of content within a topical area in an introductory materials course.

While concept maps are deemed to be a good tool to portray knowledge structure and diagnose learner's misconception, we are more interested in their integration with generic learning paradigms and in this regard, our research shows the combination of active learning strategy with concept mapping has led to plausible results for student oriented learning. Tembe and Kamble [19] have studied 414 concept maps from 207 basic school students before and after participation in one of the active learning programs (ALPs) and concluded that active learning programs helped the students to acquire new knowledge and reduce misconceptions. Yakhno et al. [20] show an increasing level of self-confidence and satisfaction among students and instructors with a new approach to Computer Engineering curriculum design based on a Module-Based Active Learning model where all theoretical knowledge in the modules is connected into a concept map. Schwendimann [21] investigates how a novel form of collaborative technology-enhanced concept map, called Knowledge Integration Map (KIM), can support students' learning from an inquiry-based, technology-enhanced evolution curriculum. Findings indicate that KIM activities can facilitate the generation of cross-connections between genotype and phenotype ideas and support students distinguishing central ideas. Fang [22] tries a non-traditional, active learning approach, in which students (rather than the instructor) construct their own concept maps in engineering dynamics, a foundational sophomore-year undergraduate engineering course. Rodrigues Da Silva et al. [23] report the results of a pedagogical strategy in a transportation course offered to Civil Engineering students that is a combination of problem-based learning and project-based learning (PBL) and blended-learning (B-learning) with cognitive maps as the assessment tool. Stoyanov and Kommers [24] provide an empirical validation of the theoretical position that concept mapping software with explicit problem-solving support performs significantly better on problem-solving and on the most of the indicators of mapping production and perceived effectiveness of concept mapping software. These results confirm the validity of concept map based active learning in higher education community, and justify our idea for using similar approach to teach system diagnosis principles.

Assessment Method

Even though concept maps have a proven track record in curriculum development and educational practices, evaluating its quality remains a challenge. Out project has some unique features concerning the use of concept maps, and thus requires a evaluation tool to better gather assessment data. There are two reasons. First, the fault diagnosis problems in the training modules are derived from actual industry experience, and our goal is to use the differences between expert map and student map to drive students for in-depth analysis of the technical problems. Therefore there needs to be a mechanism to recognize both structural and semantic differences in the maps. Second, matching two concept maps is a time-consuming and complex task because it needs to consider both the relations (links) between nodes and the content of the nodes. We hope to automate the comparison process, which means let computers dissect the results without human involvement. Several attempts have been made to facilitate concept maps comparison. Limongelli et al. [25] propose seven measures of similarity among concept maps dealing with both structural and didactic aspects of the maps. A weighted concept is proposed by Chang et al. [26] where propositions are given a weight value from 0 to 1, based on the closeness index and weighted value of each node, a similarity index is calculated for each node. Gao et al. [27] present an approach of string comparison with the meaning of the words–semantic similarity. Melnik et al. [28] presented a method called Similarity Flooding Algorithm (SFA). Our method of comparing concept maps is based on combining the weighting mechanism, SFA, and semantic similarity of two strings. The detail introduction of the method is included in the paper by Shahhosseini et al.[29].

There are two assessment tools in place for this study. The direct measure focuses on gauging the closeness of students' maps with those of the expert's, which is considered as the key indicator of their mastering of the underlying diagnosis principle and procedure. There are four test groups, one control group and three treatment groups, for the data collection sessions. Students in control group only have the map feedback from the training program. Among treatment groups, Group I has the map feedback and the expert's map, Group II has the map feedback and four meta-cognitive cue questions, and Group III has feedback, expert's map, and meta-cognitive cue questions. The results are based on upon the quantitative comparison from applying the SFA on subjects' and expert's maps. The overall similarity of the maps is calculated using the relative similarity of each nodes pair. Comparison feedback consists of two parts. One is the summary that shows the overall similarity, number of nodes in expert's map, number of nodes in learner's map, percentage of matched nodes, and the similarity range of matched nodes. The other is a color-coded similarity: darker color stands for higher similarity and lighter color stands for lower similarity.

The indirect measure aims at broader evaluation of student experience of concept map based active learning strategy. Questionnaire is commonly used for collecting cross-comparison data, and we develop a eight-qualitative-question student satisfaction survey similar to those adopted by Huang et al.[30] and Wei and Yue[9]. The data is then analyzed using only descriptive statistics.

Both training modules have identical flow and structure. The modules are a two-hour, computer-based program. The instructional shell is developed using Lectora, and the expert's map is encoded. The students are asked to create and submit his/her own concept map using open source concept mapping software Visual Understanding Environment (VUE). The first hour of this training provides the students the background knowledge of the system diagnosis principles and an opportunity to practice using VUE to draw concept maps. The second phase of the training allows the students to work on two real fault diagnosis problems. After reviewing pertinent system description and historical operational data, students are asked to develop a map to detail the steps for finding the root cause of the malfunction. In this phase, we are interested in the percentage accuracy between the student's map and the expert's map. This accuracy is not only the key indicator for assessment purpose, but also the feedback on which the students rely to revise their maps. The second round sees the re-submission be evaluated for accuracy again, and the percentage is reported back to the students and recorded for comparison with the first round results.

Assessment Results

Case Discussion The first case is a diagnostic task in electrical power generation and transmission, courtesy of Duke Energy. Figure 1 shows the concept map developed by an expert that details the diagnosis thought process in a systematic way. Students are provided with the performance data of the past thirty-six hours on a boiler, a wind turbine, and a transmission line, and are required to develop their own visual maps to choreograph how the maintenance team could use these data to pinpoint the problem.

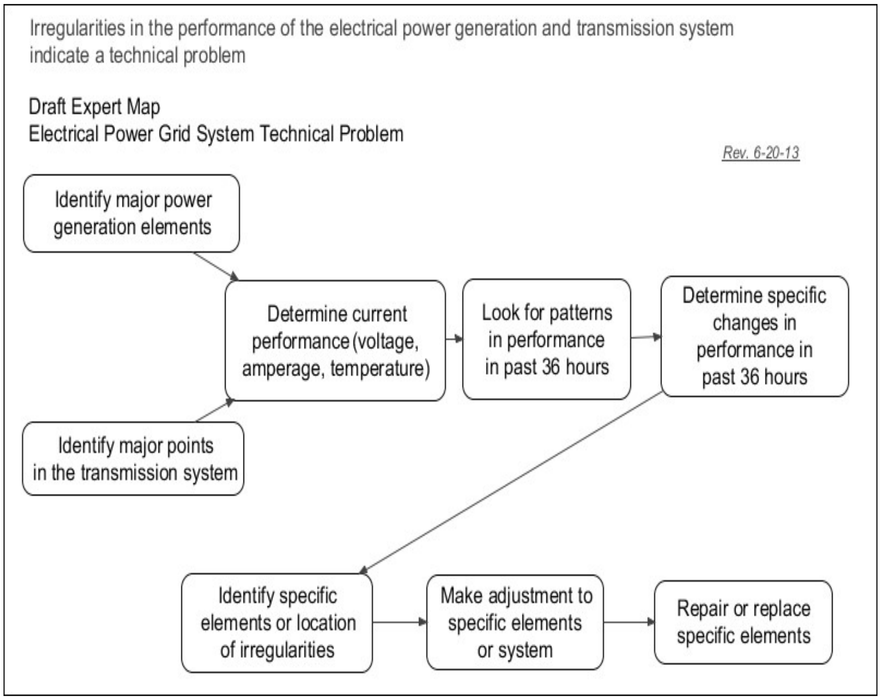

Figure 1: Expert's Map for Power Grid Problem in the Training Program

In the first attempt, the student's map has an 18% overall similarity and 38% "considerable" node similarities to the expert's map (range from 29% to 70%), as summarized in Figure 2. The student's map is shown in 3, where shade of the nodes indicates their semantic resemblance to their counterparts in the expert's map. There are three nodes with green colors. One is darker and the other two are lighter. The darker the color of the node is, the more similarity the node has. This case is from the control group, which means that the student only can see the comparison feedback before developing the second map.

After the student reviews feedback provided by the comparison program, he creates a new map shown in Figure 4. For this student, Figure 5 indicates that the second map sees an increase of 14% in overall similarity (from 18% to 32%), and 25% in the matched nodes (38% to 63%). This increase is due to the fact that the new map uses a linear structure to replace the branch layout in the first try, which makes it more inline with the expert's map.

The second case is a technical problem of a heat exchanger in a waste plastic pelletizer, contributed by Beamis, a packaging solution company at Terre Haute, Indiana. The water bath system is malfunctioning with multiple potential causes. Figure 6 is the expert's map used in the training program.

In the student's first map (Figure 7), there is a 36% overall similarity and 46% of "considerable" node similarity to the expert's map (See Figure 8). This map only has six nodes while the expert's

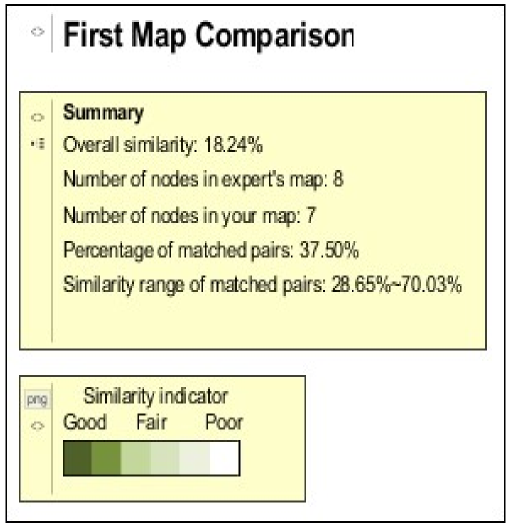

Figure 2: Power Grid Maps Comparison Summary: First Attempt

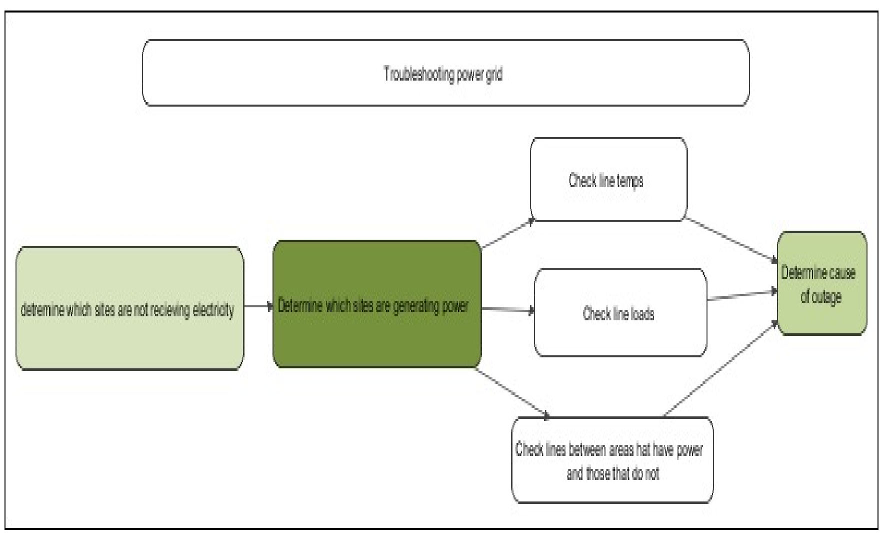

Figure 3: Student's Map for Power Grid Problem: First Attempt

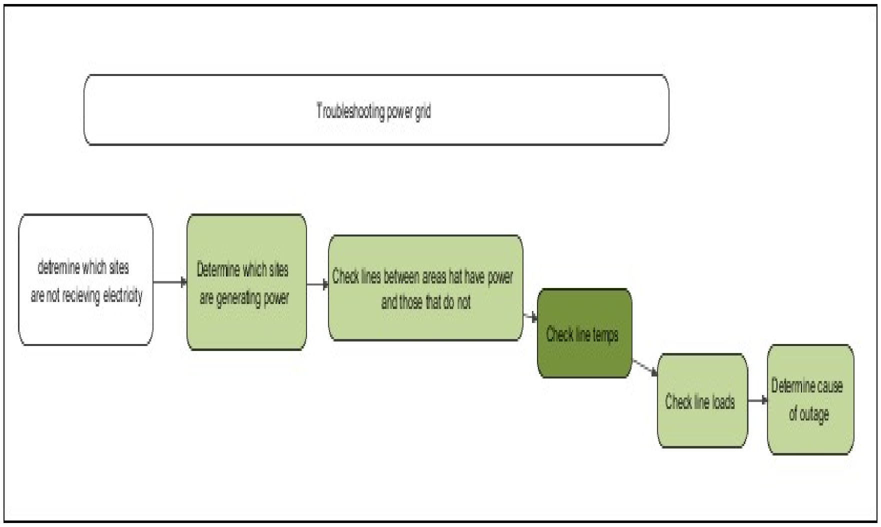

Figure 4: Student's Map for Power Grid Problem: Second Attempt

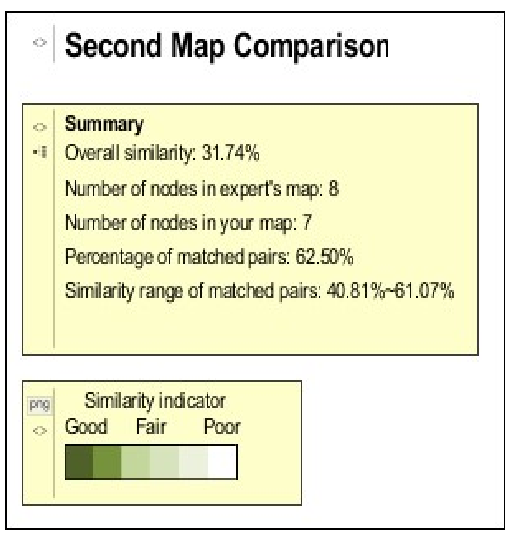

Figure 5: Power Grid Maps Comparison Summary: Second Attempt

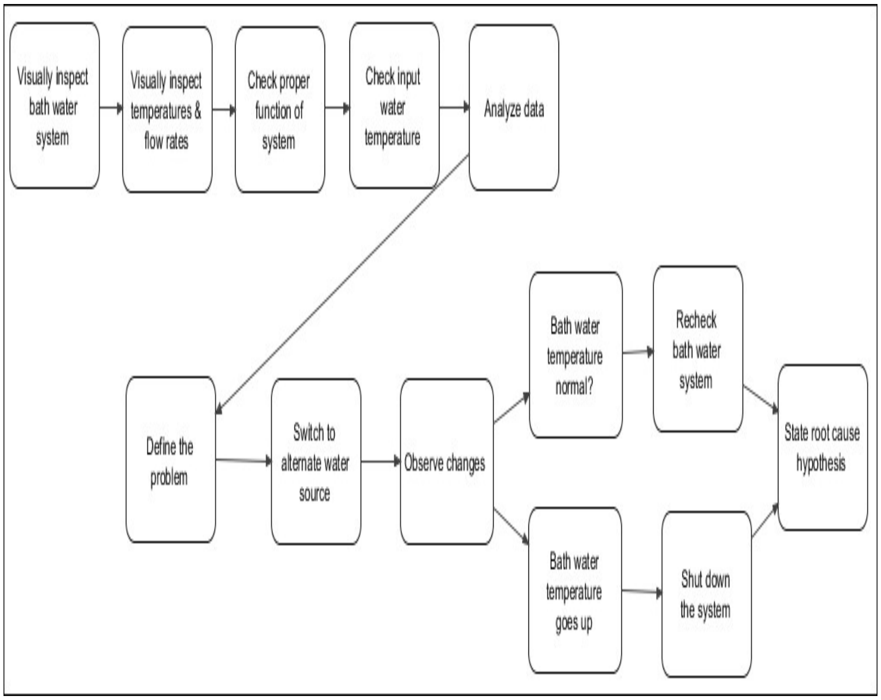

Figure 6: Expert's Map for Heat Exchanger Problem in the Training Program

map has 13 nodes. The student is in the treatment Group I, which means that the student can see the comparison feedback and access the expert's map before he makes the second map.

The second map, shown in Figure 9, contains three additional nodes that are similar to the nodes in the expert's map. The comparison summary (Figure 10) shows that the overall similarity has increased by 25% (from 36% to 61%) and the number of matched nodes has increased by 23% (from 46% to 69%). The highest similarity of an individual node, which is "Check input water temperature", is 100%.

Student Survey After completing the training program, the students are given a "satisfaction" questionnaire to provide feedback regarding their experiences with the training. The responses can be in the range of 1 to 4 for each of the eight questions asked. Consequently, the overall range for the satisfaction score is between 8 to 32. Such an approach has been tried by other researchers (for instance see Fang[22]).

Eighty students participate in four data collection sessions and complete the survey. The average score for overall experience is 3.09 out 0f 4. For question 6, most of the students "agree" ($n = 58$) or "strongly agree" ($n = 10$) that the content of the training program is meaningful; for question 7, most of the students "agree" ($n = 45$) or "strongly agree" ($n = 25$) that this training would be useful to anyone in a technical career. For other questions, most students also choose "agree" or "strongly agree".

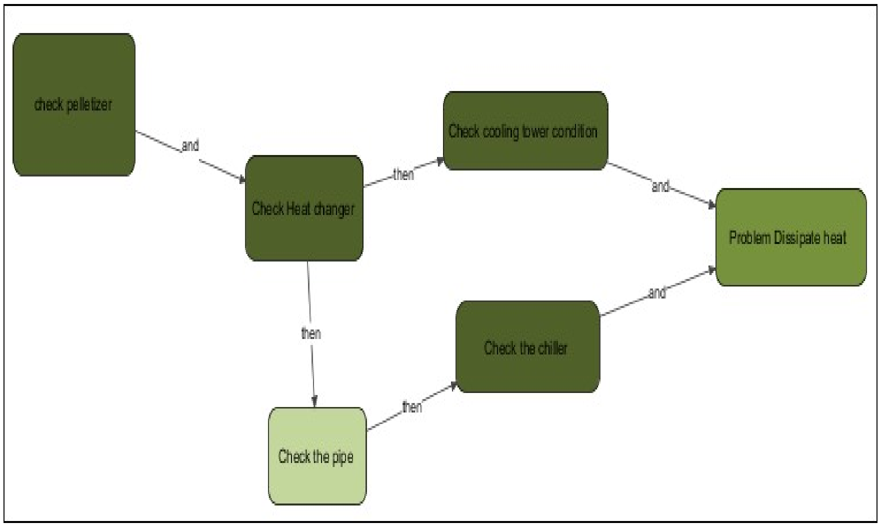

Figure 7: Student's Map for Heat Exchanger Problem: First Attempt

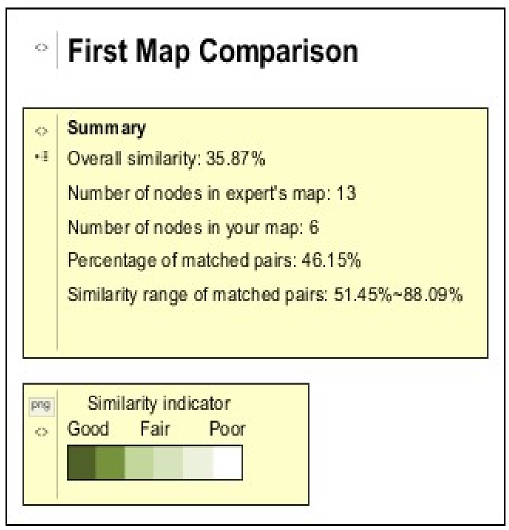

Figure 8: Heat Exchanger Maps Comparison Summary: First Attempt

Question	SA	A	D	SD	Mean	Deviation
Q1. The computer based training program was interesting	14	54	9	3	2.99	0.67
Q2. The screen design was reasonably attractive	13	57	9	0	3.04	0.53
Q3. The screen layout was logical (i.e., made sense)	25	51	3	1	3.25	0.58
Q4. All of the program buttons worked as expected	27	43	9	1	3.20	0.68
Q5. It was easy to navigate my way through the program	27	45	7	1	3.22	0.66
Q6. The content of the training program was meaningful	10	58	7	3	2.95	0.61
Q7. This training would be useful to anyone in a technical career	25	45	8	2	3.16	0.70
Q8. Overall, this was a high quality, professional experience	18	53	7	2	3.09	0.64

Table 1: Mean and Deviation of Student Satisfaction Questionnaire

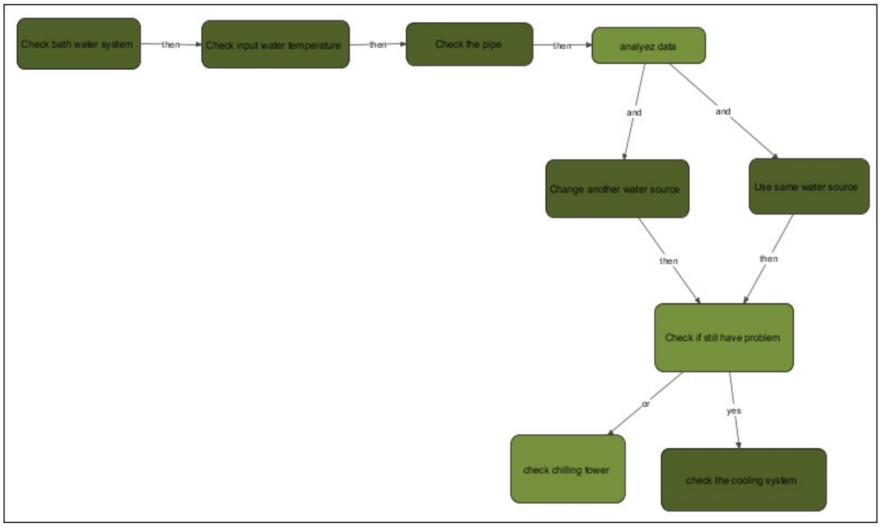

Figure 9: Student’s Map for Heat Exchanger Problem: Second Attempt

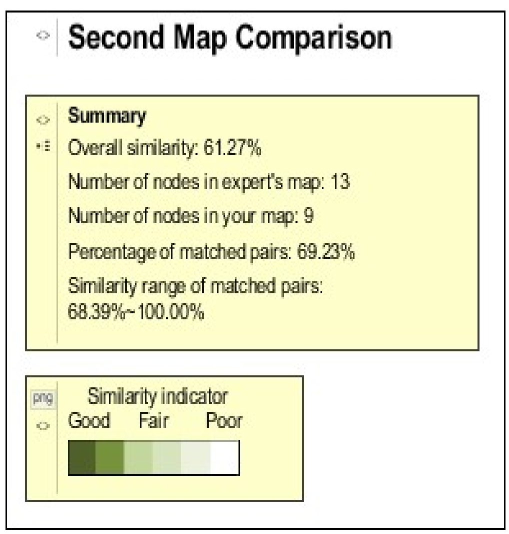

Figure 10: Heat Exchanger Maps Comparison Summary: Second Attempt

	Number of Students	Pre-Mapping Mean	Post-Mapping Mean	Post-Mapping Mean Difference	Pre- and Post Mapping Deviation
Control Group	20	0.38	0.37	-0.01	0.08
Treatment Group I	14	0.34	0.38	0.04	0.12
Treatment Group II	35	0.25	0.25	0.01	0.04
Treatment Group III	15	0.26	0.27	0.01	0.06
Average		0.31	0.32	0.01	0.06

Table 2: Mean Differences between Control Group and Three Treatment Groups

Discussion

As the survey results show, the students during pilot testing and experimentation find the training to be interesting and useful. However, on average, the students' level of performance is much lower than expected. This is certainly a surprising outcome because it differs from the findings in other literature that confirm concept maps' advantages. Only a small portion of students clearly understand and find the mapping technique and the feedback provided helping them improve their diagnostic skills. Also, there does not seem to be significant statistical difference in pre- and post mapping means between different groups, which indicates that feedback is not providing the expected guidance to students in improving their maps. We must emphasize these are still preliminary findings, therefore it would be premature to draw the conclusion based on a relatively small sample size. We do recognize a few areas of the assessment process that can be improved. For example, we notice that two hours are not enough for the majority of the students to complete the problem-solving tasks in each module. We also see the need to re-develop the survey to have the questions tied to more specific facets of the student's thought process. When it comes to administering the survey, the staff are looking at ways to assure students taking the process seriously and offering constructive feedback. With these changes, we believe the assessment data in the new cycles will be able to offer more conclusive evidence for concept map based active learning. Further, the researchers will work to expand the work to all stages in the process from problem identification to solution and follow-up assessment.

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