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Using Conceptual Mapping to Help Retain Tribal Knowledge

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many years in logistics, sales, and the financial services industry prior to entering academia. Mr. Dean has authored numerous publications while presenting regularly at national and international conferences. In addition to research and teaching, he functions as the entrepreneurial lead for the current project funded by the National Science Foundation (NSF). In this role, Mr. Dean assists the research team by offering entrepreneurial consultation, and served as the spokesperson for the group's presentations at the NSF sponsored Innovation Corps for Learning (I-Corps L) program last summer in Washington D.C. As a result, the research team was able to successfully demonstrate that the diagnostic skills training program developed during the original NSF grant could be viable and sustainable as a business training service for private industry.

Retaining tribal knowledge using conceptual mapping

Abstract

Documenting and sharing important information learned in industrial practices can often lead to significant payoffs such as reducing operational cost or improving system performance. This information, often referred to as “tribal knowledge”, is widely admitted by professional people to be of great value, and yet has not been systematically archived by most companies. In this paper, we present a conceptual mapping based approach for retaining tribal knowledge. We first demonstrate the theoretical framework for this approach that is applied to developing training modules to improve engineering and technology students troubleshooting skills. A case study of using conceptual mapping to capture domain expertise in controlling and monitoring a simulated grid developed in collaboration with Duke Energy Company is then introduced to show the validity and feasibility of the approach in actual industrial environment.

Introduction

“Tribal knowledge” is a term commonly used in industry to describe special knowledge procured through experience by only a handful of employees. These employees are usually senior personnel in the quality, maintenance, or control department in the organization, who have acquired expertise on a equipment, system, or process over an extended period of time, sometimes decades. To capture and transform this unique expertise into the company’s own knowledge base, or even intellectual property, is critical for the company’s sustainable growth.

The importance of tribal knowledge and the severity of its loss caught our attention when we participated in the I-Corps L program sponsored by the National Science Foundation and ASEE in 2015. During the course of the program, we engaged in an intensive exploration of opportunities to commercialize prior NSF TUES project on improving diagnostic skills for engineering and technology students[1]. Our goal was to identify industrial partners so that the diagnostic training programs can be adopted or adapted to tackle practical problems. During the month-long customer interactions, the team had interviewed over 100 potential clients, the majority of whom were engineers, managers, and directors of operations in heavy industry like energy, manufacturing, or health care sector. At the beginning of this process, we did not have a clear vision as to how the training modules or the underlying framework could contribute to problem solving. However, tribal knowledge emerged as the most talked-about issue in these dialogs and it became obvious that providing a plausible solution requires a different approach than what is currently in place. Some of the most revealing discoveries are:

- Most interviewees express deep concern over the loss of tribal knowledge in their respective firms.
- All but one industrial interviewee admit that their companies do not have a systematic method to collect and store the field experience of veteran employees. Most companies require their employees to routinely document the lessons learned in work, however the policy is not strictly enforced. This is mainly because the common practice for recording tribal knowledge is through internal reports, and it is widely considered to be ineffective and difficult to retrieve.
- Most companies institute the one-on-one mentoring where the new employee shadows a veteran engineer, technician, or senior personnel at work in the first six or 12 months on the job. The tribal knowledge is usually passed on during on-site training. However due to urgency of the tasks, senior engineers normally do not have the luxury to explain the thought process thoroughly during maintenance checkup and malfunction diagnosis.
- All young engineers emphasize that they are more of the “visual learner” type. They absorb and grasp domain knowledge better when they can have a mental picture of the overall system or problem at hand. They also feel that most of the time their mentoring focuses on how to resolve an individual problem, but fails to help them learn to trace the root cause of the problem that may exist in other but intertwining systems. This may often cause the inexperienced employees to jump directly to problem-solving using inefficient trial and error or opting for unwarranted large-scale parts/component replacement when being charged with similar jobs.

We also found that the loss of tribal knowledge is particularly detrimental to small businesses. Compared to their corporate counterparts, these companies cannot afford to prioritize addressing tribal knowledge problem. On one hand, they lack a rigorous process based on established quality standard such as ISO-9000 to document and maintain the information systematically. On the other hand, the companies usually do not have in place a good succession plan or training program for new workers. Therefore, if one senior employee whose working knowledge has not been properly retained leaves the company, the loss of expertise can affect the entire business/manufacturing operation; and sometimes it can lead to even more severe consequences.

Over the years there have been several studies that attempted to mitigate the problem. For instance, Spencer et al. used a form of constraint propagation within the distributed cognitive system to support the dissemination of tribal knowledge in aviation sector. Dennehy et al. presented a simple approach called “Pause and Learn” as a low-impact method of organizational learning that could foster the timely capture of critical lessons learned. However these tools either focus on sharing rather than documenting knowledge, or do not provide a mechanism to preserve knowledge cohesively and intuitively to make its inheritance easier and faster.

In summary, we have discovered through interacting with industrial people that tribal knowledge is often connected to system troubleshooting and maintenance, and has impact on reducing system downtime, improving productivity, and providing better training to new hires. We feel that it is an area where our training software for undergraduate education can find a niche. Not only is our software designed for teaching diagnostic skills, it also provides the visual representation of the problem solving, which is a feature coveted by young professionals, using conceptual maps. 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[4]. In this paper, we propose and demonstrate a concept mapping based framework that helps archive the tribal knowledge and provide more agile training tools for new employees.

Methods

Our philosophy is primarily based on Bruner's[5,6] concept of discovery learning and his connection of cognition to a theory of instruction. In order to achieve concept attainment, Bruner believes three simultaneous processes need to occur: (1) the acquisition of new information about the technical system and the diagnostic practice, (2) the application of the new knowledge to the case, and (3) verification of results (learner created diagnostic visual map) with an expert or other feedback cues.

Another cognitive and instructional theory employed is Butcher and Sumner's work on self-directed learning and sensemaking. In this case, learners use a self-paced computer-based training program to acquire a content overview of technical systems and diagnostic strategies. These learners then engage in deep-thinking to process and apply this new knowledge to create a diagnostic strategy.

Engineers and technicians have long used decision-trees or trouble-shooting guides to assist the diagnostic process while identifying problems in technical systems. In our project we have chosen concept mapping developed by Novak. Although often time a complicated and time-consuming knowledge acquisition process, conceptual mapping is nonetheless a good tool to portray knowledge structure and to diagnose learner's misconception in learning. It has been used in the development of agile diagnostic thinking skills of students who have limited content expertise[8,9,10,11]. For instance, Lee et al. applied the algorithm of Apriori for Concept Map to develop an intelligent concept diagnostic system (ICDS) to provide teachers with constructed concept maps of learners rapidly and enable teachers to diagnose the learning barriers and misconception of learners instantly[12]. Conceptual mapping has also been used in psychology[13], computer programming[14], and problem-based medical curriculum[15].

A major obstacle for conceptual mapping to gain more traction is the lack of efficient evaluation tools. Matching concept maps is a time-consuming and complex task. Different techniques have been proposed to automate the process. For example, one could use SQL data to determine the similarity while another could use XML data matching based on the hierarchical relationship between data elements.

What aforementioned techniques have overlooked is the fact that maps contain nodes and links, and consequently not only the content of, but also the relationship between the nodes is important. An effective evaluation strategy should take advantage of the wealth of information embedded in this topological structure. Therefore in this project we have developed an alternative that relies on weighting and relative similarity.

A weighted concept was proposed by Chang et al. where he gave propositions a weight value from 0 to 1. The higher weighted value a proposition was assigned, the more important the proposition was. By comparing a student's map with a teacher's (expert's) map, each node in both maps received a closeness index. Then based on the closeness index and weighted value of each node, a similarity index was calculated for each node. Using the similarity index, learner's comprehension of the node could be ranked into "learned", "partially learned", or "misconception". The limitation in this method is that the nodes in the concept maps are predefined. Students use predefined concepts and links to construct their maps, so the content of the nodes and links are not considered as a factor in comparison. The maps in our training software are open-ended maps, so the algorithms of closeness index and similarity index are not applicable. However, the weighting mechanism is still helpful to identify the importance of nodes in the expert's map.

Melnik et al. presented a method called Similarity Flooding Algorithm (SFA). SFA takes two graphs as inputs, and matches the nodes in both maps. The similarity relies on the intuition that nodes from two maps are similar when their neighbor nodes are similar. The output is a list of corresponding nodes with a similarity value. After a filter selection, the most optimized pairs are considered as the best matched nodes. SFA works on many types of graphs, such as data schemas, catalogs, xml ontologies, and concept maps. Particularly, SFA support open-ended nodes, which are required for this research. This algorithm works for directed labeled graphs, like a process map, which has arrows on links between nodes to indicate the order of the steps of a diagnosis strategy. The authors evaluated the accuracy of SFA and conclude that overall labor saving are above 50%, and actual savings might be higher.

Gao et al. present an approach of string comparison with the meaning of the words– semantic similarity. The approach uses WordNet®-based Semantic Similarity Measurement (WSSM) as the database for synonyms. WordNet® is a database of English and an open source project based at Princeton University. The authors use five steps to compute a semantic similarity for two sentences. The steps are (a) separating sentence into a list of tokens, (b) disambiguating parts-of-speech, (c) stemming words, (d) finding the most appropriate sense, and (e) computing the similarity. Although there might be many limitations, the method worked fine for this research because the target learners are supposed to be trained to use terms in their process maps.

Our method of comparing concept maps is based on combining the weighting mechanism, SFA, and semantic similarity of two strings. To compare two process maps, the comparison needs to consider both the relations (links) between nodes and the content of the nodes. The researchers used a SFA (Open source Java code developed by Melnik et al. converted the Java code to C#) to match the nodes based on their relationships. The SFA (see Figure 1) represents two input maps semantically in code first, then creates an initial map for the product of each node in both maps, calculates their similarities based on the links, and finally generates a list of best paired nodes according to the similarity of each pair. During the comparison, WordNet® is used to measure the content of nodes.

The process for comparing process maps is shown in Figure 2. The first step in the prototype

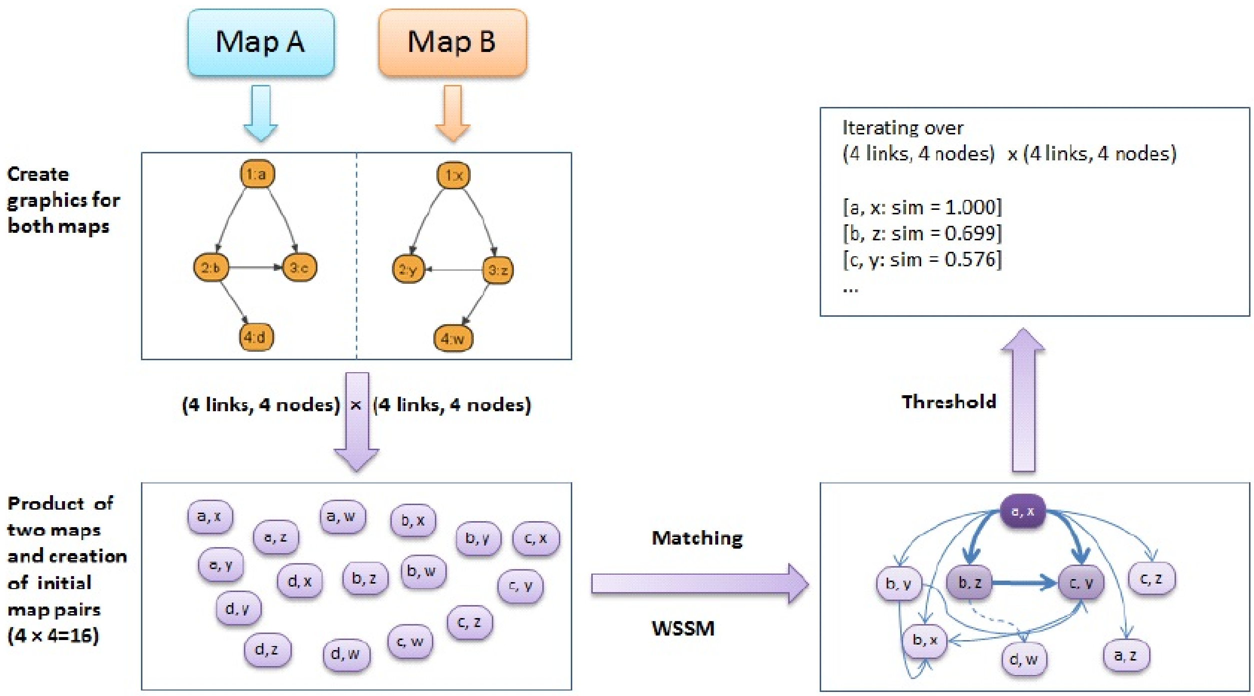

Figure 1: SFA Process

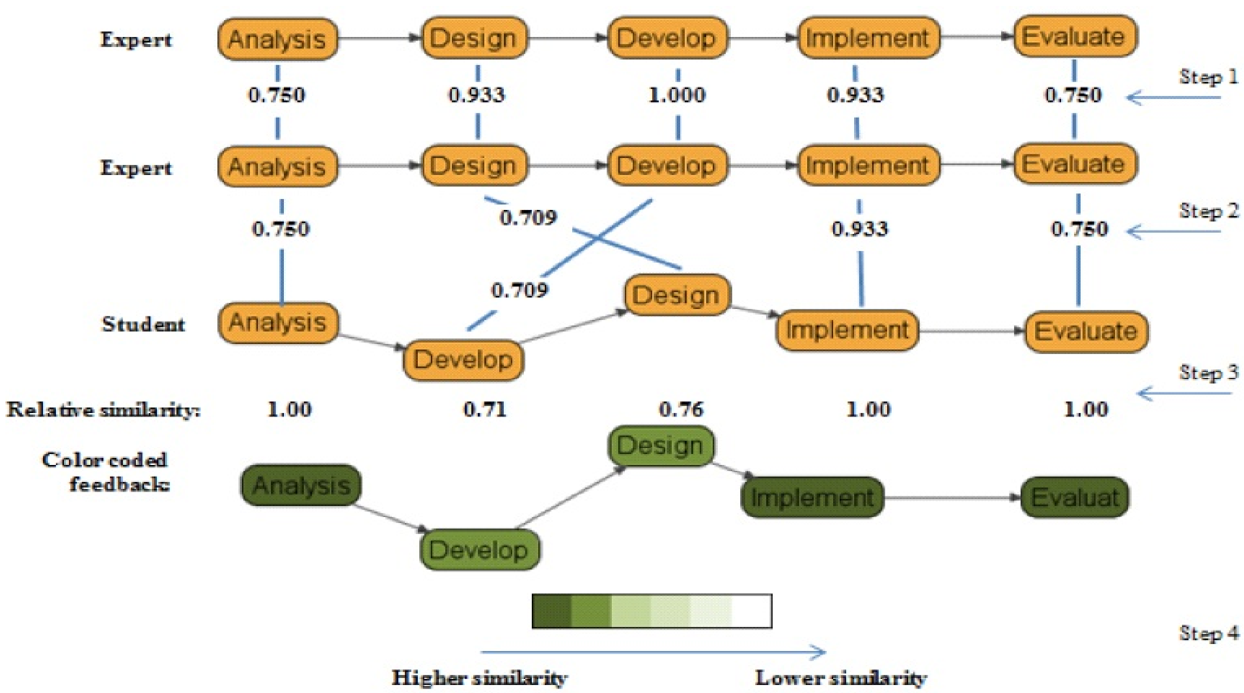

Figure 2: The process of comparison for process maps

program is to generate a reference similarity that is calculated based on the result of comparing an expert's map with the expert's map itself (s_{aee}). The reference similarity includes absolute similarity for each paired nodes, according to their links and content. The second step is to compare a student's map with the expert's map (s_{ase}). The comparison result includes absolute similarity for each node, which is considered as a matched pair with one node in the expert's map. The third step is to calculate the relative similarity (s_{rse}) for each paired nodes by the percentage of s_{aee} and s_{ase}. And, the overall similarity of the map is calculated based on the relative similarity of each pair. In this step, weighting (w) of each pair can be considered. Important nodes can have more weighting in overall similarity.

The fourth step is to generate feedback, which includes two parts. One part is a 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 part is a color-coded similarity, darker color stands for higher similarity and lighter color stands for lower similarity. A new map is generated based on the learner's map. Sometimes, the learner's map does not have a high overall similarity because it has fewer nodes than the expert's, but the feedback still could be positive because the similarities of matched pairs are strong.

The detail implementation of the framework is carried out using mostly open source software. The learner is asked to create and submit a concept map to illustrate his/her diagnostic plan using VUE concept mapping software (an open source project developed by Tufts University; http://vue.tufts.edu) within an instructional shell created in Lectora. The software has undergone field testing at multiple universities, and received an overall positive recognition. It lends the support to the validity and reliability of our desire to extend it as an interactive, stand-alone package targeting at tribal knowledge preservation.

Results

In this section, we present a case study based on a real diagnostic task in electrical power generation and transmission. The scenario was provided by Duke Energy as a collaborator on both NSF TUES Type I and I-Corps projects. Our goals are twofold: first, we show the acquisition of expert's tribal knowledge using concept maps; second, we illustrate how the preserved knowledge can be used to help students who have limited background on this specific task to gain more experience by undergoing the training program. The training program shows some information on how a power generation and transmission system works at first. Students also can access the information on performance data in the past 36 hours of a boiler, a wind turbine, and a transmission line. The task is to develop a visual map that explains how the maintenance team could use these data to diagnose the problem.

Figure 3 shows the concept map developed by an expert that details the diagnosis thought process in a systematic way. Students then develop a visual map (One example is shown in Figure 4). The darker the color of the node is, the more similarity the node has. The overall similarity is about 25%. The student's map contains 21 nodes, but only four nodes are paired with the expert's map with the range of 39% to 57%.

After the student has a chance to review his map with feedback provided by the comparison program, he makes some changes and compares the revised map with the expert map again. The result is shown in Figure 5. The second try has seen a slight improvement (about 3%) in the overall similarity. It still has four nodes that are paired, but the highest similarity score has been increased from 57% to 76%. In addition, the student's map has been simplified significantly in the second try.

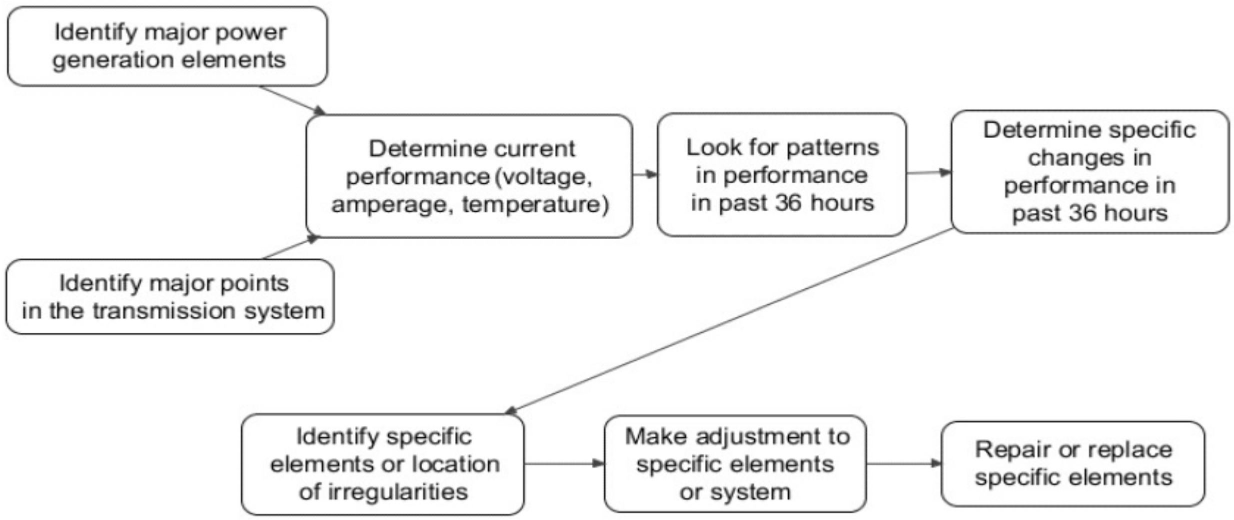

Figure 3: An expert map for electrical power grid system technical problem

Discussion

In this paper we propose a simple yet effective way to help business, especially the heavy industry to retain domain specific tribal knowledge. Tribal knowledge in many ways contains critical working experience for system maintenance, operation, and control, and therefore is very valuable for training in system analysis and trouble-shooting. Documenting this knowledge in a way that is both easier to share and comprehend can significantly impact company's sustainability and profitability. Based on a training software developed for undergraduate engineering and technology students, we present a self-contained computer-based training program that enables learners to develop visual maps of a diagnostic strategy to identify a technical problem comparable to an expert's. Several software packages, including Lectora as the primary authoring platform and VUE as the tool to create visual maps, are used. The comparison of is made following an enhanced similarity flooding algorithm.

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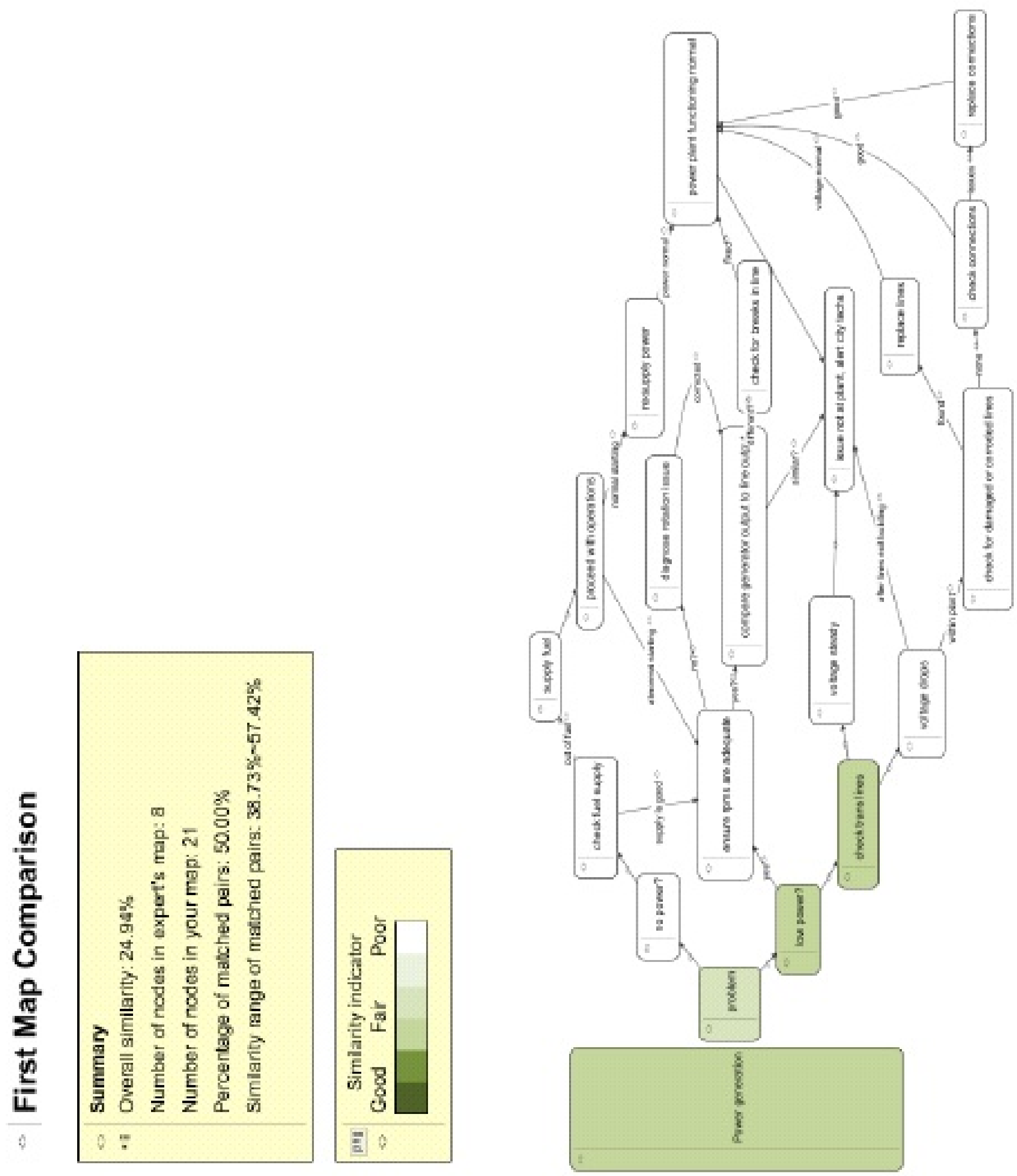

Figure 4: A student's first conceptual map of the power grid problem

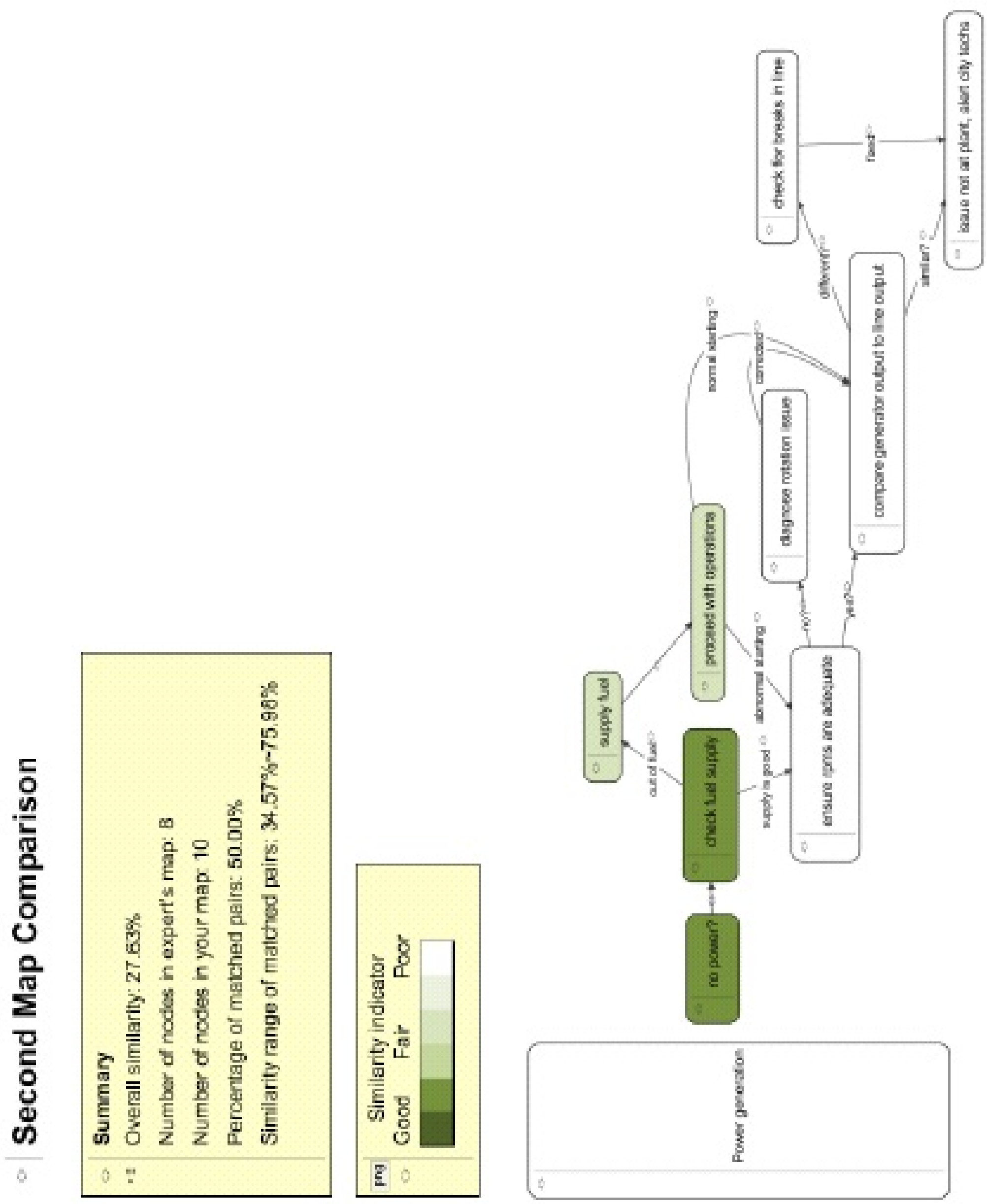

Figure 5: A student's second conceptual map of the power grid problem

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