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The Technology Interface International Journal Editors

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Evaluating Noxious By-Products of 3D Printers

Philip Weinsier, TIIJ Editor-in-Chief

Need a new car? Print one.

This is the point where I would say, Just kidding! But, in fact, a few companies have been "printing" cars for several years now. What we really mean, though, is that some percentage of the cars' parts are 3D printed and assembled by hand, while the rest are traditional parts such as engines and transmissions. Chuck Hull, known to many as the father of 3D printing, invented the process over 30 years ago. But, like most new technologies, early machines were cumbersome, inefficient, expensive, and had a limited range of processes. It wasn't that long ago that my own university had one that stood six feet tall (three feet wide and deep), cost tens of thousands of dollars, took hours and days to complete even the smallest of projects, and did not do a very good job. Just printing my name (3" letters) cost around $50 in materials (extruded plastic). But, again like most technologies, printers got smaller, better, and cheaper, and can now work with a variety of materials.

This first car—the Strati, by the Local Motors Company in 2014—strolled in as the world's first 3D-printed electric car. The 85% of the car that was 3D printed, took a mere 44 hours. The final product had a top speed of 40 mph and a range of 120 miles. Another notable entry into this category is the Blade (Divergent Technologies). Obviously, this is a larger car and only had 35% of its parts 3D printed, but it sports a 2.4 liter, 720 hp engine!

So are these cars plastic or metal? What are the 3D-printed parts made of? Like I said, 3D printing technologies today allow for the use of not only ABS (acrylonitrile butadiene styrene) plastic, but also PLA (polylactic acid), polyamide (nylon), glass-filled polyamide, stereolithography materials (epoxy resins), silver, titanium, steel, wax, photopolymers, and polycarbonate. An additive manufacturing (AM) process called selective laser melting (SLM) was specially designed for the printing of metal alloys. PLA, though, is said to be the most popular, as it is inexpensive, easy to work with, and comes in a variety of colors. But here is where the bad news enters the picture. PLA, like virtually all of the other 3D printing materials, gives off toxic fumes. PLA, itself made from maize and sugarcane, creates lactide, a toxic substance not found in nature, and which can cause respiratory and other problems if inhaled for prolonged periods of time.

This is the inherent problem with 3D printers; they function by melting the materials fed them and depositing the solution layer-by-layer to form the desired object. This heating process releases volatile compounds, some of which yield ultrafine particles that are then released into the air. And, it has been shown that the hotter the melting temperatures, the more particles are produced. Studies (Engineering & Technology Webinars, 2019) on the impacts of these particles on live animal cells indicated that both PLA and ABS had toxic effects on the cells.

If you are or plan to be involved in 3D printing—at schools, labs, offices, industrial settings—this is a must-read article for you. The author of this article (p.23) presents research results on fused deposition modeling (FDM) printers and reports on unhealthy levels of nanoparticles (1-100 nm), volatile organic compounds (VOCs), and gaseous material emissions from the 3D printing of plastics and metals. Studies on a variety of materials—ABS, PLA, PVA, HIPS, PCABS, nylon, bronze PLA, PET-based plastic materials, TVOC emissions from stereolithography, and binder jetting printing processes—found emission levels significantly higher than recommended limits.

Editorial Review Board Members

Identifying Factors that Promote Student Learning in Thermodynamics Using Machine Learning Techniques

Paul Akangah, North Carolina A&T State University; Francis Davis, Kwame Nkrumah University of Science & Technology

Abstract

Thermodynamics is an important subject in engineering training and forms the basis of pure engineering sciences. However, the performance of students in thermodynamics nationwide is poor. Not all students with high GPAs (GPA>3.0) are able to pass thermodynamics on the first attempt. The focus of this study was to understand the relationship between the success rate in the Fundamentals of Thermodynamics (MEEN241) course and the following courses as dependent variables: General Physics (PHYS241), combined Quizzes and Reading Quizzes (RRQ), Homework (HW), Tests (T), Midterm Examination (MT), Final Examination (FE), and students' prior GPA. Assignments and assessments were also designed to capture acquired skills. These assignments and assessments test high-level thinking skills, such as applying a thermodynamic principle to illuminate a problem. The research question this study tried to answer was: "How does success in RRQ and prior knowledge in thermodynamics (PHYS241) impact the success rate in MEEN241?"

To answer this question, the authors designed a machine-learning algorithm made up of a decision-tree, random forest ensemble and Naïve Bayes classifiers that could take the academic data of students (N = 111) enrolled in MEEN241 as an input. The machine-learning algorithm would make the prediction by popular vote. The machine-learning model had an accuracy of 86.49%. Class recall values for true-pass and true-failed were 90.48% and 81.25%, respectively. The class precision values for predicated-pass and predicted-failed were 86.36% and 86.67%, respectively. RRQ was the root node in six out of seven classifiers, while PHYS241 was eliminated, given that the information content was less than the 0.1 threshold. These results show that success in RRQ impacted positively on the success rate in MEEN241, while also showing that prior knowledge in PHYS241 had no influence on the success rate in MEEN241. This study suggests that student success depends on developing and constantly improving good pedagogy and good study habits.

Introduction

Poor performance on the part of engineering students in thermodynamics is chronic, prevalent, intolerable, and resistant to change (Dukhan & Schumack, 2013; Dukhan, 2016). The historic average success rate in MEEN241, Fundamentals of Thermodynamics, is 54.6% (Akangah, Parrish, Ofori-Boadu, & Davis, 2018), meaning that a significant number of students fail the course each semester. Karimi and Manteufel (2014) identified four categories of students who failed: (i) students who neither attended class regularly nor complete assigned homework; (ii) students who appeared engaged but whose efforts did not result in significant learning and, as a result, did poorly on exams; (iii) students with poor conceptual understanding of the material; and, (iv) students with weak a conceptual understanding of thermodynamics.

Although PHYS241, General Physics I, is not a prerequisite to MEEN241, the mechanical engineering (ME) curriculum is structured so that students usually take PHYS241 prior to MEEN241. However, some students do not follow the prescribed curriculum and take MEEN241 before PHYS241. The ME undergraduate student handbook describes PHYS241 as "a calculus-based physics course that covers the fundamental principles of Newtonian mechanics, heat, and thermodynamics" (Mechanical Engineering Department, 2017). About 59% of students enrolled in MEEN241 passed PHYS241, while the rest either failed or had not taken the course. It is, therefore, important to understand how prior knowledge in thermodynamics (PHYS241) helps or hinders learning and, specifically, how this prior knowledge impacts the success rate in MEEN241. This knowledge will help instructors more appropriately design instruction (Ambrose, Bridges, DiPietro, Lovett, & Norman, 2010).

After surveying important literature on pedagogy, Lin, Yen, Liang, Chiu, and Guo (2016) found that pedagogical methods and students' cognitive ability influence how students learn complex and abstract scientific concepts. Reasoning is an important human ability. Students use reasoning ability to draw conclusions and to solve problems, and this ability is a good predictor of academic achievement (Bhat, 2016). Hiebert and Grouws (2007) argue that developing students' quantitative reasoning skills requires providing them with opportunities to learn by allowing them to struggle with understanding important concepts and persisting in problem solving. Dukhan (2016) and Dukhan and Schumack (2013) identified three main learning issues that students have in thermodynamics: 1) conceptual difficulties, 2) difficulty integrating concepts and principles, and 3) not recognizing the relevance of thermodynamic principles in solving problems. Dukhan (2016) further reported that

many instructors have implemented several instructional strategies; however, student performance in thermodynamics continues to be poor and unacceptable.

The focus of this current was to elucidate the importance of prior knowledge and well-designed assignments and assessments in promoting students' conceptual understanding of thermodynamics. The study also sought to assess their ability to integrate known concepts and principles in solving thermodynamic problems. The specific aims of this study were: (i) assign reading lessons to students to facilitate the learning of thermodynamic concepts and principles; (ii) assign quizzes and reading quizzes (RRQ) designed to assess acquired skills, such as understanding of thermodynamic concepts, outlining thermodynamic problems, stating relevant assumptions, drawing schematics, drawing process diagrams, using calculus to derive equations, working from fundamental principles to solve problems, and working in consistent units; (iii) collect data on students' performance in PHYS241; and, (iv) collect data on homework, quizzes, reading quizzes, midterm exams, etc. conducted during the semester. A machine-learning model was developed to answer the research question: How does success in RRQ and prior knowledge in thermodynamics, PHYS241 General Physics, impact the success rate in MEEN241?

Methodology

The 111 participants were college students in an introductory thermodynamics class—MEEN241, Fundamentals of Thermodynamics—during the fall 2016 and spring 2017 semesters. Academic records of these students were collated, the data were randomized, and the resulting data were assigned a random three-digit number. At the start of each semester, the students' GPAs and letter grades in PHYS241 were collated. Scores in the following course tasks were compiled at the end of the semester: home-work (HW), quiz (Q), reading quiz (RQ), tests (T), midterm (MT), final examination (FE), and cumulative-weighted-average (CWA). Q and RQ were combined to obtain RRQ.

For this study, concept-intensive materials were designed and assigned as reading lessons for the students. Students took notes while reading through the assigned lesson; these notes could be used on the RQ that was based on the reading lesson. The variables Q, RQ, and T were also designed to assess acquired skills, such as defining concepts, framing problems, stating relevant assumptions, drawing schematics, drawing process diagrams, working from fundamental principles, and working in consistent units. These assessments were designed to test high-level thinking skills, such as applying a thermodynamic principle to illuminate a problem.

Data Summary: Various weights were assigned to assignments and assessments. Table 1 summarizes these weights, the frequency of various assignments and assessments, and the students' success in these assignments and assessments.

Table 1. Weights assigned to various assignments and assessments.

ASSIGNMENTS and ASSESSMENTS			STUDENT SUCCESS	
Types	Weights	Frequency	Predictor Variables	% Success Rate
HWs	10%	30	HW	83.78
RQ	5%	14	RQQ	63.10
Q	15%	16	MT	63.06
MT	20%	3	T	76.58
T	20%	6	FE	24.32
FE	30%	3	GPA (high; avg; low)	53.15; 45.95; 0.90
			PHYS241	59.46
			MEEN241 success rate	62.1%

To pass MEEN241, a student must achieve a minimum CWA of 60%. Students must also achieve a minimum of 60% on any assignment or assessment in order to pass that assignment or assessment. It is not mandatory to pass all course assignments and assessments in order to pass MEEN241. For this study, a high GPA was defined as greater than or equal to 3.0; an average GPA was defined as less than 3.0 but greater than or equal to 2.0; a low GPA was considered as less than 2.0. The success rate in MEEN241 was 62.1%, which was about 2% lower than previous studies (Akangah et al., 2018).

Data Analysis

General Physics (PHYS241) combined Quizzes and Reading Quizzes (RRQ), Homework (HW), Tests (T), Midterm Examination (MT), Final Examination (FE), and students' prior GPA. To answer the research question, the RapidMiner (2017) data analytics platform was used to develop a machine-learning model that consisted of three algorithms—decision tree, random forest, and Naïve Bayes. RapidMiner is an integrated extendable environment for machine learning, data mining, text mining, and predictive analytics platform and has excellent drag-and-drop graphics capability. It has powerful algorithms capable of solving many analytics problems. RapidMiner comes in both free and commercial versions. The free version was used in this study. Table 2 shows the attributes or predictive variables ranked by information gain. Information gain was based on the reduction in entropy after a dataset is split on an attribute and is a measure of a reduction in uncertainty. Information gain measures the association between inputs and outputs as well as the relevance of an attribute. Entropy is a probabilistic measure of uncertainty or ignorance.

Table 2. Attributes ranked by information gain.

Attributes	Information Gain
RRQ	0.288
FE	0.241
MT	0.186
T	0.161
GPA	0.136
HW	0.069
PHYS241	0.042

Because the information gain of HW and PHYS241 was less than the threshold value of 0.1, it was subsequently dropped. Correlation between the remaining attributes was examined and the results revealed no strong correlation. Three classifiers were designed that take these attributes as inputs to predict the success rate in MEEN241. Prediction was based on the voting system. Figure 1 shows the basic concept.

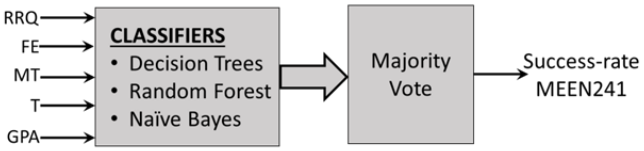

Figure 1. Conceptual model to predict success rate in MEEN241.

Decision Tree with Cross-Validation

A decision tree (DT) with cross-validation was optimized with respect to maximum depth, criterion, apply pre-pruning, and apply pruning. The optimized parameters obtained were: maximum depth of the decision tree—6; criterion—accuracy; apply pre-pruning—true; and apply pruning—false. This model included three subsets derived by using a linear sampling method. In the cross-validation method, two subsets for training the DT and one subset for testing were used. A minimum 0.1 Gini index gain, a measure of impurity or entropy of a node based on observed probabilities, was used. A confidence of 0.1 was used in making predictions based on the decision tree. This parameter specifies the confidence level used for the pessimistic error calculation of pruning (RapidMiner, 2014). The pessimistic pruning method uses pessimistic statistical correlation test (Quinlan, 1993). A random forest classifier generates several DT ensembles, and it does not over fit model to data. In a case of a classification problem, the classifier outputs the class that is the mode of the classes, and in the case of a regression problem, it outputs the mean prediction of the individual trees. The classic bootstrap method was used in this study, where three subsets were created at random with replacements from the original data. RapidMiner randomly selects the variables and decides on the best split to the node. This method does not prune the trees. A minimal Gini index of 0.1 and a confidence of 0.1 were used in this study.

The Naïve Bayes classifiers represent a family of simple "probabilistic classifiers" and denote a supervised learning method in addition to a statistical method for classification. The method applies the Bayes' theorem with strong (naïve) independence assumptions between the attributes. It assumes a certain probabilistic model to calculate uncertainty about the model in a vigorous way by determining probabilities of the outcomes. It is capable of solving diagnostic and predictive problems. Bayesian classification provides practical learning algorithms and can combine prior knowledge with observed data. It calculates explicit probabilities for hypothesis and it is robust to noise in the input data. Figure 2 shows the process diagram for the ensemble algorithm.

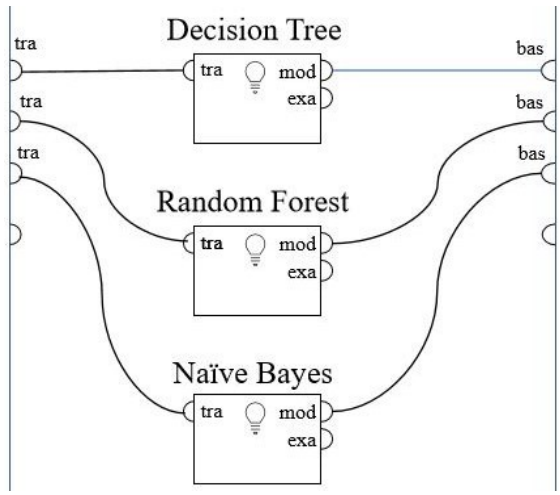

Figure 2. Machine-learning ensemble model comprising decision tree, random forest and Naïve Bayes methods.

Results

Data Summary

Figures 3 and 4 show the boxplot distributions of the dependent variables. Table 3 shows the confusion matrix. The machine-learning model had an accuracy of 86.49%. The class recall or sensitivity values for true-pass and true-failed were 90.48% and 81.25%, respectively. Class recall, which was expressed as a percentage, was defined as the ratio of relevant instances that were retrieved over the total amount of relevant instances. The class precision or positive dependent values for predicated-pass and predicated-failed were 86.36% and 86.67%, respectively. Class precision was defined as the ratio of relevant instances among the retrieved instances. Figure 5 shows a schematic of the details of the decision tree. The highest node in the tree, RRQ, is the root node and represents the attribute with the lowest entropy or uncertainty. The tree was built by first determining which attribute could best separate an impure node into children (internal) nodes that would be more pure than the parent node. This attribute was then used to split the node.

The children nodes were FE and T. This process was repeated until a node was pure or too small to be split further, producing the leaf nodes—FAILED and PASS. A number of different criteria could have been employed in this calculation; however, the Gini index criterion was used in this study.

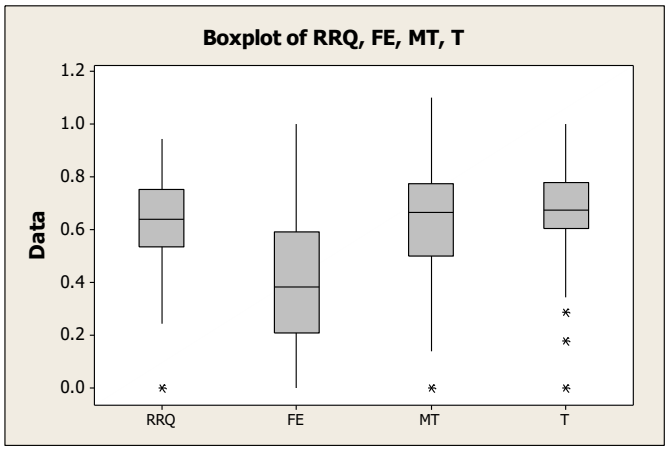

Figure 3. Distribution of the students' assignments and assessments by GPA.

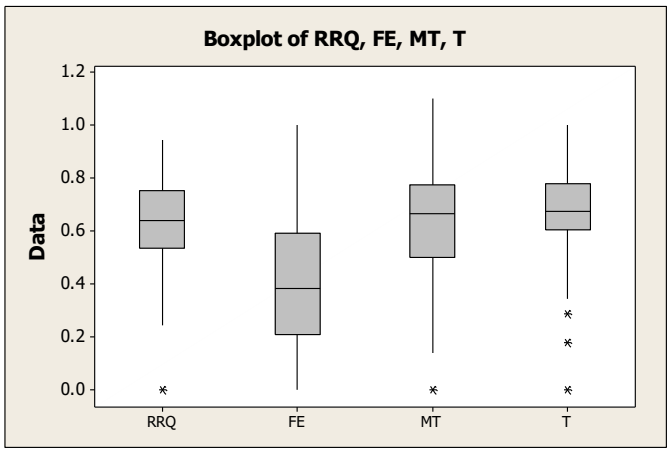

Figure 4. Distribution of the students' GPA.

Table 3. Confusion matrix of ensembled machine-learning algorithm.

	True PASS	True FAILED	Class Precision
Predicated PASS	57	9	86.36%
Predicated FAILED	6	39	86.67%
Class Recall	90.48%	81.25%	

The class label of an impure leaf was obtained from the highest occurring value of the target variable or class; this value is indicated beneath the leaf node. The decision tree predicted that, out of 62 students who passed both RRQ and T, 54 students (87.1%) would pass MEEN241. Of the eight students who passed RRQ but failed T, six (75%) failed MEEN241. A similar analysis could be conducted for the other branches. Figure 6 shows six (a-f) different decision trees generated for this study, using stratified sampling with three subsets in order to guarantee that the distribution of the class in the subsets would be the same as that in the whole dataset.

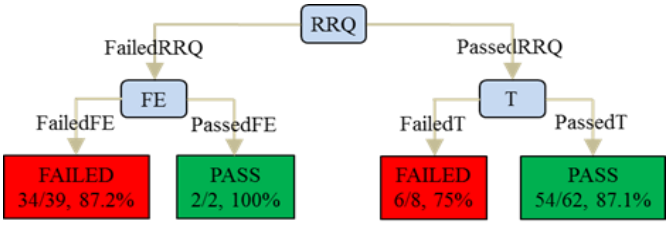

Figure 5. Decision tree with cross-validation.

Of the six random forest decision trees, five had RRQ as the root node, while the remaining tree had MT as the root node. Taking the decision tree in Figure 6(e) as an example, the two students who passed RRQ but failed T and had high GPAs also passed MEEN241. More than half of the 111 students (53.15%) had GPAs equal to or greater than 3.0. Furthermore, all students with an average GPA who passed RRQ and failed T also failed MEEN241. However, the number of students with high or average GPAs who passed or failed MEEN241, respectively, were too small to draw any conclusions.

Discussion

In this research study, the authors looked at the manner by which the dependent variables, GPA, RRQ, T, MT, and PHYS241, affected success rate in MEEN241. The success-rate in MEEN241 was 62.1%, which was about 2% lower than previous studies (Akangah et al., 2018). Thus, class assignments and assessments were designed in line with the problem-solving approach shown in the course textbook (Cengel & Boles, 2002). Resources such as teaching assistants and the instructor's office hours were also accessible to students to promote learning. In addition, students periodically received reading assignments. A machine-learning algorithm to explore the relationship between dependent variables and success rate in MEEN241 was developed. The model had a good accuracy of 86.49%. The model correctly predicted 57 true-pass out of 63 cases and correctly predicted 39 true-failed out of 48 cases. In this study, one of the objectives was to understand the impact of the dependent variables on the success rate in MEEN241. Therefore, a model with a high class recall and precision was needed. Class recall values for true-pass and true-failed were 90.48% and 81.25%, respectively. Class precision values for predicted-pass and predicted-failed were 86.36% and 86.67%, respectively. Although a high class precision value for predicted-pass was needed, the difference was statistically insignificant.

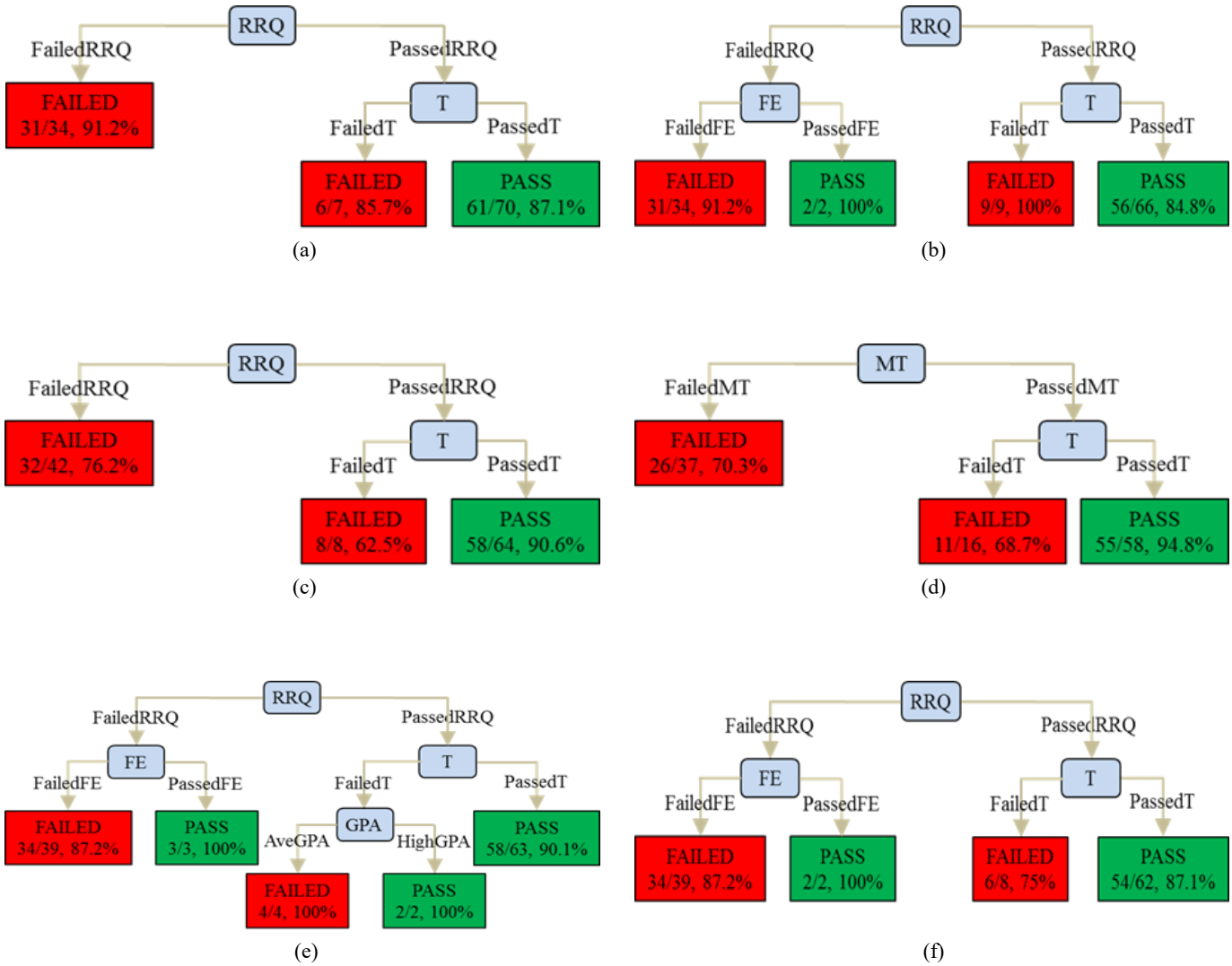

Figure 6. Random forest decision tree ensemble.

The information content in HW and PHYS241 was uncertain and, as a result, information gain was less than the threshold of 0.1. This discovery was found to be quite alarming. Akangah et al. (2018) determined that HW assignments were not helpful, because students usually either copied from the solution manual or did not complete the assigned HW. This finding contradicts the general belief among school leaders, teachers, and parents that homework is a useful educational tool (Falch & Rønning, 2011). HW is influenced by many factors and effective HW design can promote student learning (Pelletier & Normore, 2007; Planchard, Daniel, Maroo, Mishra, & McLean, 2015; Bas, Senturk, & Cigerci, 2017). HW assignments are given for tutorial purposes, such as offering students the chance of reviewing or practicing material that has already been presented in the class. When students copy from the solution manual or fail to submit their HW, then the process is circumvented and the system fails. When students struggle to grasp important concepts and persist in problem solving, students develop reasoning skills, and that promotes academic achievement (Bhat, 2016; Hiebert & Grouws, 2007).

It was determined, however, that prior knowledge in PHYS241 had no influence on the success rate in MEEN241. Even though the curriculum of PHYS241 deals with some of the basic concepts in thermodynamics, such as heat, and should impact the pass rate in MEEN241, it did not seem to do so. This finding is in accordance with conclusions made by Akangah et al. (2018). The information gain in PHSY241 (~0.042) was low, and there was no association between success in PHSY241 and success in MEEN241. Ambrose et al. (2010) concluded that students'

prior knowledge can either help or hinder their learning, but the data in this current study does not support this conclusion and further suggests that course content in PHYS241 has no relevance to thermodynamics. The authors of this current study recommend a curriculum review to understand this discrepancy. The research results indicate that success in RRQ positively impacts the success rate in MEEN241. RRQ had the highest frequency of testing among the dependent variables. Frequent classroom teaching had a significant effect on student achievement. Many researchers agreed that, when done right, frequent testing helps students retain concepts longer (Bangert-Drowns, Kulik, & Kulik, 1991; De Paola, & Scoppa, 2011; Karpicke, 2012; Carpenter, 2012; Einstein, Mullet, & Harrison, 2012).

The information gain in GPA was higher than the threshold value of 0.1; however, the information gain was not high, and GPA was, therefore, not a very useful attribute for predicting the success rate in MEEN241. GPA was not a root node and only made it as a branch node in one out of six decision trees. GPA was a vital parameter employed in admissions and job recruitment decisions among others. Notwithstanding all of these findings, several studies have indicated that GPA can easily be predisposed to reporting biases (Felton & Koper, 2005), tenure of faculty members (Karimi & Manteufel, 2013), student-faculty interaction and desire to excel in college (Lambert, Rocconi, Ribera, Miller, & Dong, 2012), and students engaging in part-time work during the semester (Dundes & Marx, 2006). As a result of these influences on GPA, it is therefore not surprising that GPA was not the most important factor in predicting which students passed MEEN241.

Conclusions

In this study, the authors assessed the correlation between success rate in MEEN241 (56.76%) and the following dependent variables: General Physics (PHYS241), combined quizzes and reading quizzes, homework, tests, midterm examination, final examination, and students' prior GPA. To rank the dependent variables and eliminate variables with information gains less than the threshold of 0.1, the entropy method was used. The resulting dependent variables were T, MT, FE, GPA, and RRQ. Class assignments and assessments were designed to evaluate acquired skills, such as understanding of thermodynamic concepts, framing problems, stating relevant assumptions, drawing schematics, drawing process diagrams, using calculus, working from fundamental principles, and working in consistent units. These assignments and assessments test high-level thinking skills, such as applying a thermodynamic principle to illuminate a problem. The problem-solving method was built on the strategy described in the textbook. Reading assignments were given frequently, followed by RQ. A machine-learning model was developed to answer the research question: "How does success in RRQ and prior knowledge in PHYS241 impact the success rate in MEEN241?" The model had good accuracy, class recall, and class precision. The models were, however, found to be slightly better at predicting success rate than fail rate. This capability was welcomed, as one of the objectives was to understand the effects of the dependent variables on the success rate in MEEN241.

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Engineering Applications in Precision Agriculture

Suxia Cui, Prairie View A&M University; Yonghui Wang, Prairie View A&M University

Abstract

As one of the greatest inventions of the last century, the computer has immeasurably changed our everyday lives. Recent techniques, such as embedded systems, data cloud, and autonomous applications, are examples of but a few of the many computer technology applications. One of these areas of implementation is in the field of agriculture. The agricultural industry faces a challenging task of sustaining the world's growing population. Through the use of well-timed information gathering and proper decision-making technology, this task can be facilitated with modern technology (Cui, Wang, Risch, & Bourgeois, 2014). With the help of improvements in electrical and computer engineering, precision agriculture and smart farming have been raised to new heights. In the meantime, educating the younger generations about how to apply their engineering skills in agriculture is also crucial. In this paper, the authors present cases of funded projects to enhance engineering education in precision agriculture, including both prototype design and real system implementation. Students obtained training on embedded systems design, robotics, data cloud, and Internet of Things (IoT) techniques, as well as problem-solving skills.

Introduction

The world's population has already exceeded 7.7 billion, while agricultural land is not increasing. This brought a great burden to the agriculture industry (Blanco, 2016; Goecker, Smith, Fernandez, Ali, & Theller, 2015). How to increase the productivity of agricultural fields is a problem for every country. Over the past few decades, several developed countries, including Japan, Germany, Canada, and the US, have searched for answers using precision agriculture (PA). One example of PA approaches adopts advanced techniques from electrical, mechanical, computer, and other engineering territories to design an intelligent decision system to assist farmers in irrigation, fertilization, pest control, and other human labor-intensive tasks. (Corrigan, 2017; Krambeck, 2016; Li, Simonian, & Chin, 2010; Mahlein, 2016; Precision Agriculture, 2018). Research statistics show that the US made several achievements with PA and, as a result, profit can be gained from selling more food and fiber than is import from other countries (Human Capacity Development, 2009). To be able to sustain a positive agricultural trade balance, the US Department of Agriculture (USDA) sponsored many research and educational projects on PA. The authors of this current study were able to obtain one funded project from the USDA entitled, "Establish an Intelligent Equipment Lab for Precision Agriculture at Prairie View A&M University (PVAMU)."

This three-year project was well implemented. In this case, "intelligent equipment" means computerized information and communication technology (ICT) and a decision support system (DSS), which monitor the field and control the devices with internet connectivity (Bourgeois, Cui, Wang, & Obiomon, 2015; Immenschuh, 2014). Through this capacity-building grant, the PVAMU team was able to explore necessary ICT platforms on an automatic irrigation system. Microcontroller and sensing technologies were tested in the automatic irrigation system, as faculty and undergraduate and graduate students were able to receive PA training. Teaching modules were developed for undergraduate classes, and undergraduate students' capstone designs were supported for three consecutive years. All those efforts equipped PVAMU graduates to be competent for jobs in agricultural industry. In this paper, the authors share their experiences during project implementation, with a focus on two capstone designs in a sequence of three. Since the first capstone design led to a master student thesis, the details were published (Bourgeois et al., 2015; Cui et al., 2014).

System Design

This capacity-building grant was funded in 2012, when there were not many autonomous systems implemented in this rural area of Texas. Thus, a prototype was first designed in the established intelligent equipment lab with indoor testing of the proposed system. During this period, faculty and students received experience from other funded projects of network communication. Wireless sensor network (WSN) was the chosen technique to support system information transmission (Kim & Evans, 2009). National Instruments' (NI) WSN kit has compatible humidity and temperature sensors that were easily implemented into the system. Figure 1 illustrates the hardware components in the system. There were two sensors that were connected to the NI WSN nodes. The signals obtained by the sensors were sent to an NI WSN gateway, which was connected to a workstation. Mobile devices were then connected to the system via the internet.

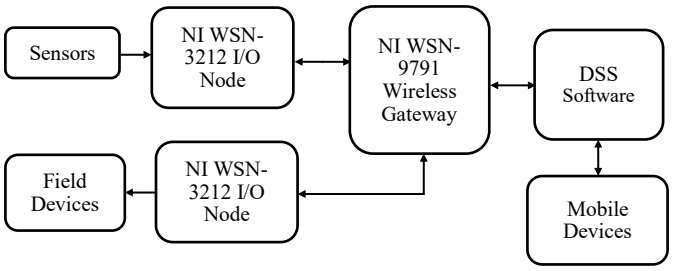

Figure 1. NI WSN-based system diagram.

In addition to hardware, software was also important for this design. NI has its own programming environment with a drop-and-drag feature. LabVIEW software communication was vital to this project and was used to continually monitor real-time temperature readings from the sensor node transmitted by radio frequencies to the gateway node, then to iCloud via Ethernet. The LabVIEW software DSS handles the commands to the NI Dashboard, which relays back to the smartphone for user-friendly monitoring and control. On the sensing side, NI's WSN-3212 thermocouple measurement node receives temperature and humidity information and continuously monitors the data. An information control module was developed using LabVIEW WSN and embedded on the measurement node. This control module compared the collected real-time data with a predefined threshold. Anytime data exceeded the threshold, a transmission action would trigger a warning signal. Figure 2 shows the procedure and logic relationship among hardware components, as indicated by the sampling programming diagram.

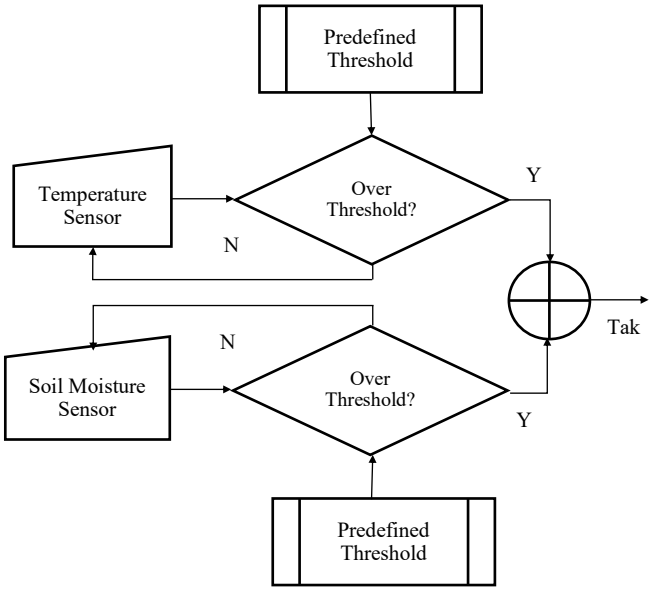

Figure 2. Sample LabVIEW thermocouple temperature control programming diagram.

By sending only important data, the user conserves power and extends battery life. The system has a simple logic model for decision making. Similar to the temperature programming diagram, scaled values from raw data and set points from mobile devices are compared in the DSS program and the result triggers the output. Following are the smart decisions included in this design:

- Condition: Humidity Set Point > Actual Humidity Decision: Water Pump ON and Low Humidity Alarm ON
- Condition Humidity Set Point < Actual Humidity Decision: Water Pump OFF and Low Humidity Alarm OFF
- Condition: Temperature Set Point < Actual Temperature Decision: High Temperature Alarm ON
- Condition: Temperature Set Point > Actual Temperature Decision: High Temperature Alarm OFF

Data Cloud and Mobile Devices

Two highlights of this design include a user-friendly interface for mobile devices and cloud data storage. Cell phone and iPad applications were built using Dashboard Application Building software. The following features were used on the display.

- Sliders were chosen to set the temperature and humidity set point values.
- Numerical indicators as well as a bar graph displayed current humidity and temperature values.
- Digital values, such as pump on/off, humidity alarm on/off, and temperature alarm on/off, were displayed on LEDs.

Figures 3 and 4 show interfaces for computers and mobile devices, respectively.

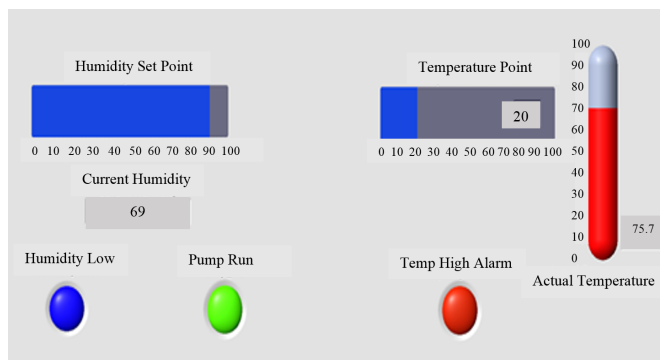

Figure 3. System interface for computers/workstations.

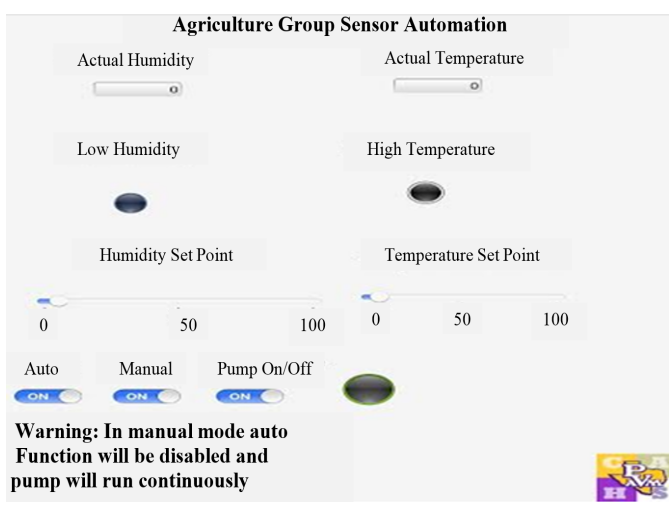

Figure 4. System interface for mobile devices.

With innovations in technology and special equipment provided for engineers, the way to access, send, and receive information has become expeditious throughout the years. One of those ways is to implement the data cloud. The data cloud allows users to not only store but also retrieve necessary information. NI provides a technical data cloud to support its products. Authors utilize the data cloud for storage when receiving information from the sensors that are out in the field. Figure 5 shows the system designed in a classroom for this study; a display board was built with three light bulbs representing the remote-controlled switches that could be turned on and off via mobile devices. At the bottom of the board are two NI WSN nodes, each connected to one sensor. The two sensors, one for temperature and one for humidity, were compatible with NI nodes and had a functional range of -40 to 70 centigrade. These two values were collected to determine the need for irrigation. Each WSN node could cover a range of 100 meters. A simple electrical circuit was placed in the middle of the board to support the system with enough power to drive servos for real-life applications. The system was demonstrated to both engineering and agriculture undergraduate classes as an example of how electrical engineering and computer science can help in precision agriculture. Feedback from students was very positive.

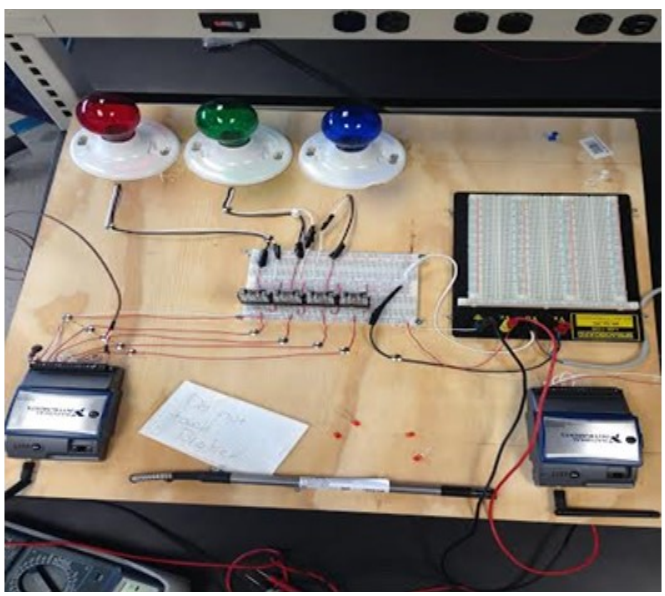

Figure 5. Display board for system demonstration.

Real Outdoor System Implementation

After the prototype was tested and proved effective, the next step was to adapt it for field testing. But there were two reasons for switching to a new microcontroller-based system. One was the fast development of embedded systems over the past decade, where ARM, Arduino, and PIC microcontrollers were integrated in most devices to add intelligence to them (Brain, 2000). The other reason was that NI stopped support for the Dashboard and Data Cloud. The following year, another senior design group took it over to redesign the system using Arduino and Raspberry Pi. More advanced technologies were adopted in the system's design to demonstrate how electrical engineering and computer science can move the concept of PA forward.

Features of New Design

The focus of this current project was still on the collection, sharing, and application of agriculturally relevant information using precision technology. Some of the current technologies used in the industry are unmanned autonomous rovers. These vehicles carry devices and sensors in order to collect and transmit information vital to agricultural end users. Luckily, another USDA-funded capacity building grant, which ended two years ago, successfully designed a model for a remote-controlled vehicle for the field of agriculture. The mechanical structure can serve as the starting point of the rover, while the autonomous feature is the key to be developed in this project. The team had researched various technologies used for these purposes and designed a system for the autonomous collection of soil moisture data over a predefined channel using GPS that would be transmitted to the cloud via a wireless ZigBee 802.15.4 mesh network. The project also featured a fixed weather station that would have a line-of-site wireless connection to a microcontroller-based access point using the ZigBee protocol. This fixed station could provide weather data to the user, while also serving as a connection point for the autonomous vehicle's ZigBee transceiver.

Data collected by both systems were uploaded to the cloud where data could be accessible via web application. This time, a public data cloud was chosen to serve as the remote storage location. Additionally, the autonomous vehicle would alert the user when a data point falls outside of the user defined parameters. The user would then have a choice to take action or decline the action based upon that data.

Microcontroller-Based System Design

As mentioned earlier, a microcontroller was the dominate technique for this system. First, the authors created a microcontroller-based weather station that would wirelessly transmit local weather information to the user's mobile device. This information should include basic weather data such as temperature, relative humidity, wind speed, wind direction, and soil moisture content. This weather station was also self-powered by a solar panel. It was understood that this information was location specific and would be used to decide if conditions were suitable for unmanned autonomous rover (UAR) use. An Arduino Uno with a ZigBee module was sufficient to drive this system. Figure 6 shows the system diagram. All of the components were connected with direction of information flow.

Next, the UAR was designed to autonomously navigate a user-defined area, in a user-defined pattern, or to user-defined waypoints, in order to collect data. The user received data wirelessly from the UAR on a mobile device via a web-based application in order to have a choice of taking action via the UAR based on the data received. This was the most challenging part of this project. Besides the Arduino Mega, a Raspberry Pi was added to the system to improve the computational power for GPS and cloud access. Figure 7 shows the circuit block diagram.

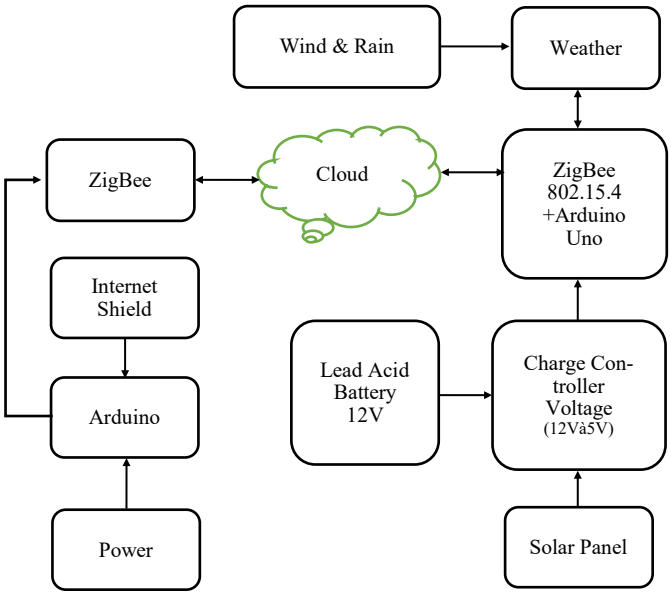

Figure 6. Weather station block diagram.

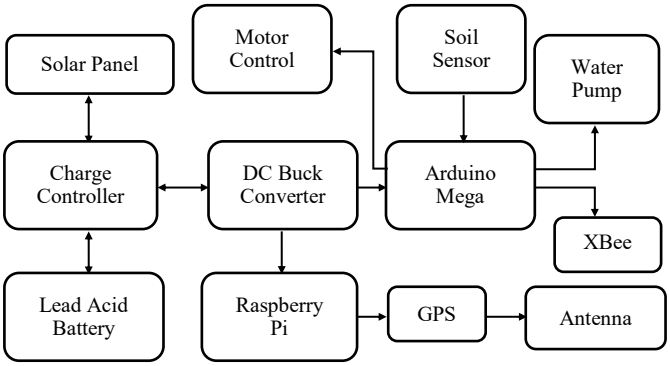

Figure 7. UAR circuit block diagram.

Mobile Interface and System Testing

Because the second part of the design was targeted at real products in the agriculture field, the whole system was tested in an outdoor location. Figure 8 indicates how the weather station was able to transmit temperature, humidity, and other weather information to a cell phone.

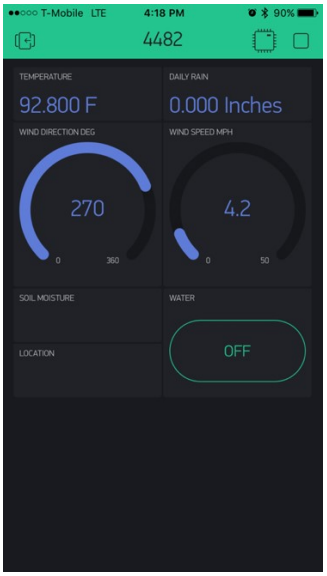

Figure 8. Mobile interface.

If the UAR is enabled to go into the field and use the attached sensor to detect the soil moisture, the UAR location and soil moisture information will also appear on the cell phone. The irrigation action was realized by turning the button on or off under the "WATER" section on the panel. Figure 9 illustrates the final product of the system design: a weather station and a rover. It was designed such that the weather station could report the user data collected from the farm on a daily basis. At the same time, all information would be transmitted and stored in data cloud. If some predefined threshold could not be satisfied, or the user chose to do a certain task, the rover could be sent out to a certain location with GPS guidance. Soil moisture information would be sampled when the rover arrived at the location from a robotic arm that would dip into the soil. Of course, based on all of the data collected, the irrigation system could be triggered automatically or manually by the user. The system was designed to be able to function autonomously and obtain and transmit crucial data in order to assist in decision making on crop irrigation. Field tests showed that it met these expectations. This platform was ready to support various applications, such as fertilizing or pest control, by changing the sensors and action mechanism, based on agricultural scientists' suggestions.

Educational Activities

Besides the aforementioned products, verifying the technical efficiency of this project and its educational role was another important aspect. This three-year project provided training for faculty, graduate students, and undergraduate students. First, faculty members involved in the project, who came from three colleges—engineering, agriculture, and arts and sciences—were able to enhance their research and teaching expertise in the area of precision agriculture.

They were able to collaborate more closely and new proposals were submitted together to extend the precision agriculture research. Three graduate students were supported under this project. They worked on three research projects towards their theses: 1) Arduino microcontroller-based IoT system design; 2) Autonomous robotics system; and, 3) wireless sensor network-based ICT system design. All of them have publications on their various topics. Each year, two undergraduate students were hired by this project to conduct research projects. They helped faculty members to develop the ICT and DSS systems. Their works were disseminated to PVAMU research annual symposiums.

(a) Weather station

(b) UAR

Figure 9. Final system design.

Each year, one senior design group was supported by this project to work on the ICT and DSS for precision agriculture. Their topics included: 1) develop a LabVIEW-based WSN system for precision agriculture; 2) design a real-time sensing system for data collection from the agricultural field; 3) design an Arduino microcontroller-based autonomous data-collection system with IoT. Their designs and reports were highly rated at the end of the senior design presentation. All of the modules developed for these projects were introduced in undergraduate agriculture, engineering, and technology classes. Class surveys and student interviews showed positive results. Throughout the entire process, students gained hands-on experience with technologies of various engineering disciplines, including agricultural, electrical, and computer engineering. Students increased their confidence in pursuing future career opportunities. Also, student feedback showed a positive impact on expanding their knowledge and skills in information technology and for agricultural applications.

Conclusions and Future Work

This project was well implemented and it was the only project chosen to be included in the grant brochure to represent USDA Capacity Building support to Prairie View A&M University for the past five years. Overall, the design served to demonstrate the benefits of autonomous vehicle technology and the importance of information communication technology in the agriculture industry. Such systems should serve users by saving time and money and helping them precisely apply agricultural inputs and harvest the resulting outputs in a more efficient manner. There are several findings authors would like to share:

- Precision agriculture is the future trend for producing sufficient food for human beings.
- Multidisciplinary researchers should be involved—electrical engineering and computer science can play an important role in developing an applicable real-life system.
- It is crucial to educate the next generation on how to utilize their knowledge in the development of precision agriculture.

In the future, there will be more cutting-edge technology added to this system. For example, drones (Colin, 2016; Faine, 2016) can add another dimension of freedom and more remote-accessible sensors to guard the field and can reduce response time for decision making. To summarize, one of the major challenges faced by many industries including the agricultural industry is that of population growth. The challenge to the agricultural industry is twofold: sustaining a healthy population, while balancing vital resources such as water, petroleum products, and land. This makes the application of precision agriculture technologies particularly important in that it allows agricultural users to apply these resources more effectively and efficiently.

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Exploring the Effects of Light and Contrast on the Capability of Industrial 2D Vision Systems

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Masoud Fathizadeh, Purdue University Northwest

Abstract

In this study, the authors explored some common problems and solutions concerning the effects of lighting and color contrast on the capability of industrial 2D vision systems. The 2D vision system was used in combination with an industrial, multipurpose robot to demonstrate how these factors might affect the capability of the vision system and the overall results on the robot's performance. An industrial robots are frequently used for sorting, packaging, material handling, part separation, and assembly purposes. This type of robot relies heavily on the visual data gathered by its vision system to carry out the parts of these tasks that cannot be performed using rigid programming alone. The vision system's only means of gathering visual information is by the reflected light it captures, which is highly sensitive to factors such as surface textures, materials, angles of lighting, and contrast.

Introduction

An industrial robot is capable of performing a vast range of tasks alone, but these tasks are dependent on rigid programming that can limit the robot's capability. With the installation of a 2D vision system, the robot has the advantage of acquiring visual data through a camera, analogous to a human eye (David, 2019). This has significant benefits that cannot be programmed into the robot, such as the ability to recognize physical properties including an object's shape, size, color, and features. However, there are problems and limitations, as the camera's ability to translate these features is entirely dependent on the reflected light the camera receives. This reflected light can either help or impair the vision system, depending on a multitude of outside factors (Khoshelham & Elberink, 2012). When the camera captures images of an object in front of it, the object's surface texture, background, material, color, and shape can all significantly affect the quality and accuracy of the vision system's recognition. (Mahmud, Joannic, Roy, Isheil, & Fontaine, 2011).

In this study, the authors explored some of these factors affecting the vision system's capability and what effects they might have on the robot's combined performance. Some of the variables explored were angle of ambient light, the surface texture of the object identified, and the color/contrast between objects and their backgrounds. The authors reviewed and verified the effects of lights and contrast on the capability of industrial 2D vision systems. They also demonstrated the effect of angle of light on the quality of the image captured by the robot's camera. Finally, they verified the effects of light and contrast on the grayscale value and quality of the image.

Methodology

The analysis of this concept was carried out by cross referencing multiple scholarly resources for reference in addition to performing experiments using an industrial robot and vision system. Figure 1 shows the experiments that were performed using a FANUC LR Mate 200iD 4s industrial robot.

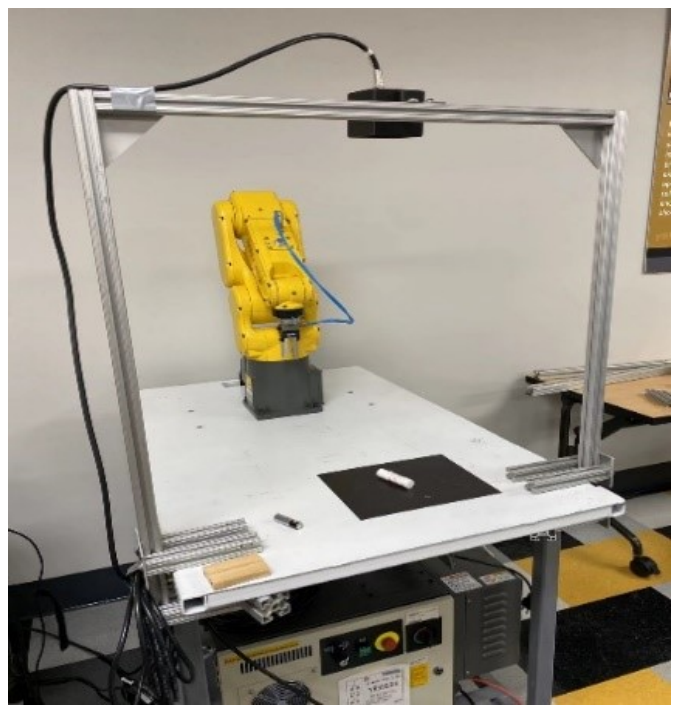

Figure 1. Experiment setup.

This robot was a multipurpose, articulated robot combined with a 2D, black-and-white camera for the robot's vision system. The camera used in this research was a GigE Basler digital camera. The wavelength range of the light source used for this camera was 400-900 nm, and the frame rate speed was 50 fps. Using various types of materials and lighting positions, the vision system was programmed to recognize various objects, while lighting variables were manipulated to observe effects on its ability to accurately

and reliably find the objects. The robot was programmed to pick and place the object, which depended on the vision system to tell it the location, orientation, and type of object it was. If the vision system the robot relied on could not identify an object in the robot's view, it would be incapable of performing even this basic task (Ifees, 2019).

Angle of Light

Because the vision system was essentially an "eye" for an industrial robot, the vision of the robot was dependent on the amount of reflected light it received, much like a human eye. This light, unless controlled or manipulated, can come from multiple angles and may not always compliment the object being evaluated, and could even make the desired vision process impossible. An example from National Instruments showed a smooth, convex plastic bottle and a smooth, metal jar lid being inspected using a black-and-white 2D vision system (National Instruments, 2019). This example demonstrated the significant effect of altering the angle and reception of reflected light on the vision system's image quality. In those images, having the light directly over the product resulted in the surfaces' properties reflecting light in a way that did not enable the vision system to adequately inspect the products. Both surfaces were smooth and abnormal, which caused the camera to receive high concentrations of light in certain areas, thereby making the vision system incapable of recognizing other critical details such as the label. In another image from that same test illustrated significant improvement in image clarity simply by changing the angle of the lighting to be near parallel to the surface.

Images taken in this current study yielded results similar to the National Instruments' findings. Figure 2 shows a rectangular jungle block with a flat, coarse texture, while Figure 3 shows a AA battery with a round, smooth texture. Figures 4 and 5 show the objects found by the vision system when the light was at an angle of 90 degrees to the surface.

Figure 2. Rectangular block.

Figure 3. Round shape.

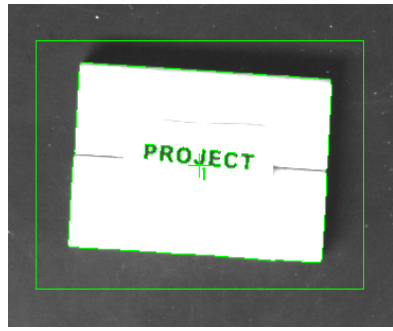

Figure 4. Rectangular block at 90-degree lighting.

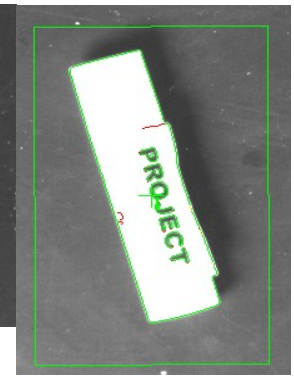

Figure 5. Round block at 90-degree lighting.

Notice that the surface of the rectangular block is completely reflective, resulting in the logo being invisible to the vision system, while the shape is well defined due to its high contrast compared to the background. The battery experienced a similar issue, because its surface had a reflection that impaired the camera's ability to clearly read the logo. Figures 6 and 7 show the same objects located with the vision system, except that here the angle of lighting was changed to 60 degrees from horizontal. These two images demonstrate the benefit of changing lighting angle with either of these textures. The coarse surface was not as intensely reflective, allowing the vision system to locate the logo, and the battery's logo was significantly better defined with the new angle.

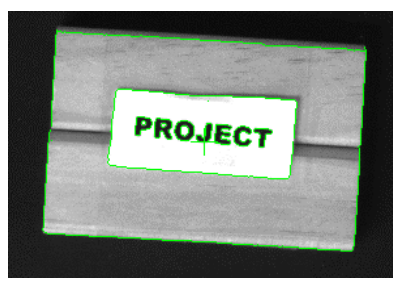

Figure 6. Rectangular block at 60-degree lighting.

Figure 7. Round block at 60-degree lighting.

Color Contrast in Grayscale

Another scenario that demonstrates the significance of light and contrast is when a vision system is needed to differentiate between objects by color rather than by physical features such as shape or size. As the industrial vision system in this study only operated in grayscale, it was essentially only concerned with a value of brightness between black and white, corresponding to an 8-bit digital output camera with a value between 0 and 255. Due to this restriction, the vision system did not recognize color and relied only on surface brightness. The brightness of an object

compared to its background was defined as its contrast, and this value of contrast is what was used to define the location and features of an object. Figures 8 and 9 show how, during experimentation, three pairs of equally sized rubber erasers were placed within the vision system's view.

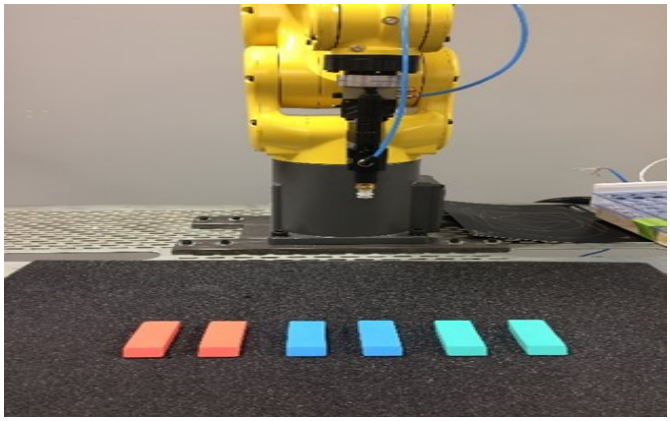

Figure 8. Erasers placed in the camera's field of view.

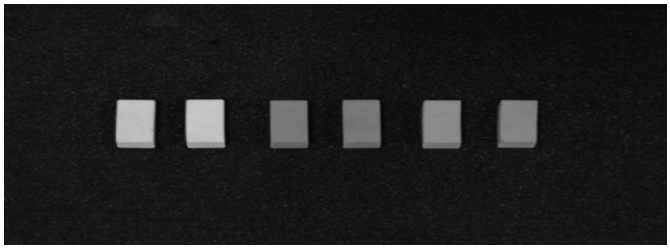

Figure 9. Snapshot of the same erasers using a grayscale vision system.

The erasers shown were all the same except for their color; one pair was red, another pair was blue, and the third pair was turquoise. The red and blue pairs were selected because their colors differed noticeably, but the turquoise pair varied from the blue only slightly, making them presumably more difficult to differentiate. Notice in Figure 9 how the three pairs of erasers in the same orientation appear when viewed using the vision system. The red and blue have a noticeable difference in brightness, meaning the vision system was able to determine a noticeable difference in their contrast, but the turquoise pair had virtually no noticeable difference from the blue pair, making their contrast more difficult to differentiate. The results were quantifiable in their determined value of contrast, which ultimately defined whether the camera was capable of performing the task sufficiently. In this experiment, the robot was able to identify each object, but was not always capable of differentiating between them, especially with the two pairs of cool-colored erasers. This occurred because the contrast of the red objects (being higher at around 120/255) was easily identifiable, while the blue's contrast (approximately 72/255) and the turquoise's contrast (approximately 60/255) were too similar to consistently separate.

There are methods of overcoming this, however, such as using different vision tools during setup of the vision system or even using a different type of lighting, such as white, blue, and green light. The vision system could be programmed using methods such as the histogram tool to search out and identify the specific range or value of contrast desired for a particular object. Each object having a different mean value of contrast could be found by programming the vision system for that particular range. Another solution would be to use a different type of lighting system. The effect can be improved by using incandescent, fluorescent, halogen, or LED lighting, depending on the requirement, because each of these lights emits a unique wavelength and the recognized object color and contrast results from the type of wavelength it reflects (Chatterjee, 2016). Another method is the use of wavelength-manipulating filter adapters that can be used over the lens of the camera to help emphasize or mask certain colors. Images can be taken with different filter adapters to produce the desired outcome given the object that is to be detected (National Instruments, 2019).

Optimal Contrast for Inspection

Often times only a basic visual inspection of an object is required to analyze an object's shape or size. Such a process is not concerned with surface features, logos, or textures; therefore, these features do not need to be taught to the vision system. If the object in view has many features on its surface or certain surface textures, this may result in the vision system performing identification and location of the object poorly. Figure 10 provides an example of this in which the vision system is taught to search for a coin.

Figure 10. A coin taught to the vision system with overhead lighting and no modification.

Notice how the vision system automatically recognizes and learns the intricate patterns in the surface of the coin due to the textures and lighting. The problem is that these complex patterns reduce the capability of the vision system. When the coin is moved or rotated, the reflections and contrast distribution on the face of the coin change enough to reduce the findability of the object. Also, the additional features require more time to identify and are not required for shape and size processes, making them entirely detrimental for this purpose.

Two solutions to this issue are using mask/emphasis areas or implementing a more effective, complimentary lighting method. The use of mask and emphasis areas can be sufficiently effective for some applications, but for an example such as this coin, it will still not yield optimal results. For example, Figure 11 shows how the coin's surface features were all masked to prevent the vision system from searching for them and an emphasis was placed on only the coin's outer edges to focus on its shape and size. This helps the accuracy of finding the coin, but the edges of the coin have a lip and texture that continues to reflect light differently depending on its orientation, which results in the same problem as before. Implementing a different method of lighting, however, can prevent this issue entirely by changing how the vision system recognizes the object. One such method is using backlighting as opposed to overhead lighting. Figure 12 shows how backlighting places the light source under the surface the object rests on, which results in the elimination of unwanted reflections from the object's surface as well as any detrimental reflection from the surrounding background.

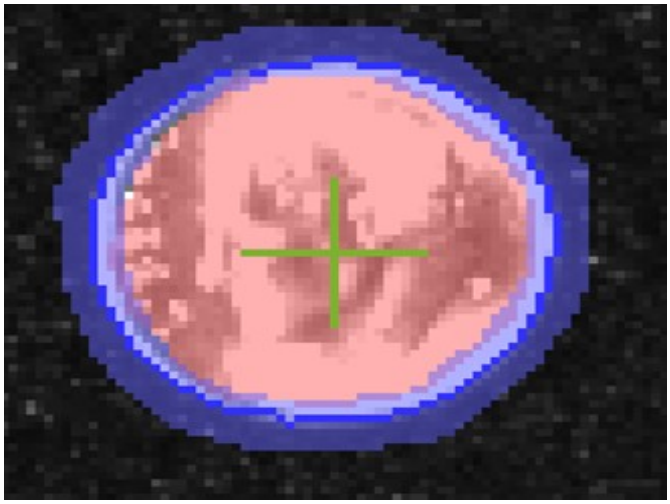

Figure 11. A red mask area and blue emphasis area placed over the coin.

The vision system can now locate the object only as the area of light that it blocks. This results in only giving the vision system the information required, shape and size. This one change improves both the accuracy of each object found and also reduces the amount of time required to find the object.

Conclusions

An industrial 2D vision system relies on light for every pixel of information it gathers and, as the eye of the robot, the robot is equally reliant on the accuracy and reliability of its vision system. To achieve the most robust vision system, a proper understanding of what is required of the vision system and how to manipulate the light received is paramount. Consideration of the object's surface texture will reduce the time required to locate or inspect it as well as improve the reliability of the vision system by giving the camera the best context in terms of environment. If the surface texture cannot be manipulated (as it rarely will be able to), the angle of incoming light can be manipulated to compensate and reflect the light back to the camera in a more advantageous way.

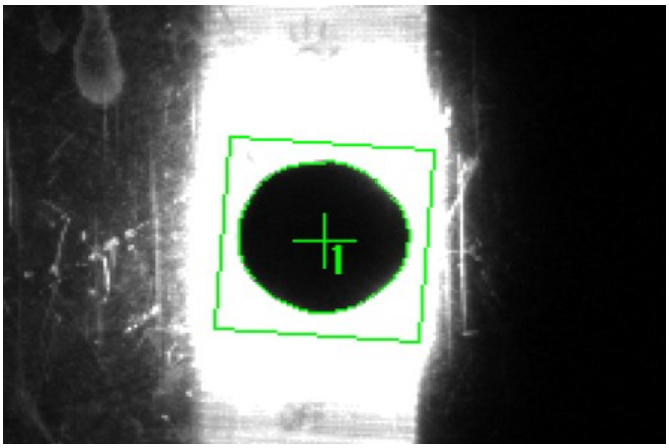

Figure 12. Under-table lighting for the same coin.

If a color vision system is not within the confines of the budget or can otherwise not be obtained, there are ways to achieve adequate results equipped only with a black-and-white vision system. Adjusting the type and calibration of vision tools in the vision system's software can enable it to inspect objects using a criterion that will overcome its inability to determine color to some extent. Additionally, a different type of light as well as wavelength-manipulating filters can be combined with the vision system to assist in the detection of color-specific contrasts in objects. Grayscale values can be interpreted and translated differently from values based on the color, contrast, and brightness of the objects and their background. However, the combination of all of these characteristics can affect the gray values. Moreover, the gray value is determined by the difference between the absorbed and reflected amount of light.

Finally, tailoring the vision system's operating conditions for specific purposes can provide the greatest results and functionality. If the function of the vision system is solely for size and shape analysis, for example, the method of lighting can be altered to enhance only these features while suppressing other unnecessary details. The use of backlighting is one method that can avoid the detection and interference of any surfaces that cause inconsistent or complex patterns of reflected light. Identifying a complimentary method such as this can even reduce the time required for the vision system to locate the object. Clearly, lighting angle, color of the object, surface texture, light color, filters, and backing light factors have a huge impact on the image sensed by the vision system.

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Is 3D Printing Safe? A Literature Review

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Abstract

Safety of 3D printing technologies is a major area of concern, as new materials and printing technologies are continuously evolving. Most research on the subject has focused on emissions into the air during printing activity. In the literature, there is an ample amount of study about the emission characterization of most common 3D printing technologies available at schools, labs, and in-office areas. Numerous researchers have studied fused deposition modeling (FDM) printers and reported unhealthy levels of nanoparticles (particles in the range of 1-100 nm), volatile organic compounds (VOCs), and gaseous material emissions from 3D printing of plastics and metals. In those studies, the most researched materials were acrylonitrile butadiene styrene (ABS), polylactic acid (PLA), PVA, HIPS, PCABS, nylon, bronze PLA, and PET-based plastic materials. Researchers also studied total volatile organic compound (TVOC) emissions from the stereolithography and binder jetting printing processes and found emission levels significantly higher than recommended limits. The most recent studies focused on case studies, surveys, and experiments on lab subjects. The goal of this current literature review was to collect and analyze the results of published research studies on the safety of 3D printing technologies. Selected studies were further organized in a tabular and graphical format to present a clear comparison of findings with respect to baseline standards. Finally, a summary of recommendations is provided for common health issues related to 3D printing processes.

Introduction

3D printing is a form of additive manufacturing (AM), a process in which bodies of components and assemblies are constructed layer by layer by adding one cross-sectional layer at a time. The cross-sectional shape data come from a computer-aided design (CAD) model. The technology is unique in its ability to create end-use parts directly from raw material with no or minimal need for pre- or post-machining steps. Any 3D geometry developed by 3D modeling software, no matter how complex the shape, can be printed in solid 3D form. In its early stages, thermoset polymer-based brittle materials were the only available materials for 3D printing of parts. For that reason, the technology was used mainly for the rapid prototyping of components and assemblies for visual product evaluations. In the last three decades, the technology has experienced substantial advancements. Today's 3D printers are faster and more precise, and many printing technologies are capable of printing at 0.1 mm layer thickness. In recent years, AM technologies have become capable of industry-level production with the introduction of industrial-grade printing materials (Huang, Liu, Mokasdar, & Hou, 2013).

Today, printing technologies are capable of printing parts from stainless steel, titanium, aluminum, ABS, PLA, and many other industrial materials. Although AM technology is still behind traditional mass-production methods in terms of precision, surface finish, and speed, it is a feasible alternative when various business strategies such as custom design, low-volume production, distributed manufacturing, occupational safety, and sustainability are prioritized (Huang et al., 2013; Chan, Manoharan, & Haapala, 2017; Jiang, Kleer, & Piller, 2017; Frazier, 2014; Kreiger & Pearce, 2013). From an economic point of view, employing AM technologies becomes justifiable for various high-end production areas such as the healthcare industry, airplane and luxury automotive industry, and jewelry industry, where the cost per unit of product is typically high. (Vandenbroucke & Kruth, 2007; Chan et al., 2017; Uhlmann, Kersting, Klein, Cruz, & Borille, 2015; Burkhart & Aurich, 2015).

As AM technologies and systems have become more prevalent in manufacturing facilities, laboratories, schools, and office areas, the safety of AM technologies has been attracting more attention from researchers. The focal point of this study was to review the literature on potential human health risks associated with 3D printing technologies. The results of this study will be able to inform and guide future users of 3D printing technologies about safer practices at homes, schools, and office areas. It was also intended to help establish new research and effective policy development opportunities in identifying and preventing health risks associated with AM technologies.

Literature Review

The review of the subject was based on the online search of Google, Google Scholar, and multiple databases available through the university library, such as Environment Complete, Research Library (Proquest), SciFinder Scholar, Web of Science, Academic Search Complete, and Science and Technology Collection. The search was performed using different combinations of the following terms: 3D, print, health, safe, hazard, harm, emission, effect, additive manufacturing, VOC, UFP, and occupational health. These terms were searched in the "keywords," "abstracts," and "titles" of the sources. Finally, references of existing research were analyzed as well. Since this was a literature review of the existing body of knowledge, the search was not limited by any criteria or source. The sources used for the research included peer-reviewed publications, technical papers, book chapters, technical/scientific magazines, and news sources related to the effects of 3D printing processes on human health. The summary of the literature review was organized according to the types of 3D printing technologies and materials. The search resulted in the collection of findings on

emissions associated with fused deposition modeling (FDM), stereolithography, binder jetting, laser sintering, and metal 3D printing process. In the last section of this paper, the results of the case studies and surveys are summarized.

Fused Deposition Modeling

Fused deposition modeling (FDM) technology builds components by melting and extruding material onto a platform. The most common materials used are ABS and PLA plastics. Because of its low cost and ease of use, FDM is the most common AM technology used for rapid-prototyping purposes at schools and engineering companies. Thus, most of the available research is dedicated to the analysis of health risks related to the operation of FDM systems. Despite the great potential of the FDM process, research studies have shown that heating of materials during FDM processes above 200°C could expose the users to hazardous particles emitted from the thermal decomposition of plastic input materials. There were numerous studies performed after Stephens, Azimi, El Orch, and Ramos (2013) published the first study on desktop 3D printing emissions. The majority of these studies focused on hazardous emissions of ultrafine particles (UFPs, particles smaller than 100 nm in diameter), volatile organic compounds (VOCs), elements, and metal to air.

When UFPs are inhaled, it takes less than one minute for the particles to reach the brain and the human bloodstream. Through the bloodstream, they can reach and be accumulated in the liver and spleen. Wright and Kelly (2017) discussed how plastic particles are resistant to chemical degradation and can translocate across living cells and impact the immune system and health of cells. In the literature, there is evidence about the common diseases associated with UFP absorption, such as bronchitis, tracheitis, asthma, and some forms of cancer (Merlo & Mazzoni, 2015). In a study by Vance, Pegues, Van Montfrans, Leng, and Marr (2017), the authors characterized the emission of aerosols during the FDM 3D printing process using a controlled chamber. The analysis was performed for particle sizes from 14.6 nm to 680 nm using value ABS, premium ABS, PLA, wood-infused PLA, and copper-infused PLA. They measured average aerosol emission rates as $1.08x10^{11}$/min, $1.25x10^{10}$ /min, $1.48x10^{10}$/min, $1.10x10^{8}$/min, and $1.58x10^{8}$/min, respectively. Aerosol emission factors per gram of plastic material used were measured as $6.2x10^{11}$, $7.8x\ 10^{10}$, $7.6x10^{10}$, $5.7x10^{8}$, and $6.4x10^{8}$, respectively.

Stabile, Scungio, Buonanno, Arpino, and Ficco (2017) also performed an emission analysis of the FDM printing process using ten different PLA blends in a 40 m^3 room. They studied the particles of sizes from 6 nm to 220 nm at various temperatures ranging from 180°C to 240°C. They reported that the emission rate increased with the increase of nozzle temperature, and at 240°C, the emission rate ranged from $4.18x10^{10}$ to $2.78x10^{12}$ particles per minute. In contrast, the emission rate was found to be negligible below 220°C. Zontek, Ogle, Jankovic, and Hollenbeck (2017) studied the emission of UFP and nanoparticles ranging from 2 nm to 10 μm during the printing of ABS parts at 213°C. They conducted the test in a poorly ventilated room of 3m x 9m x 6m with 1.8 air change per hour. They measured particle concentrations around 104 particles/cm^3. The researchers were also able to identify some of the emitted aerosol components as cyclohexane, n-Decane, 1-Decanol, and isocyanic acid, which have adverse health effects such as irritation and cardiovascular disease.

Rao, Gu, Zhao, Sharmin, Gu, and Fu (2017) measured $PM_{2.5}$ particle emissions from FDM printing of ABS parts at 270°C. The analysis of $PM_{2.5}$ particles was performed by a haze detector having a measurement range of 0-1000 micrograms/m^3. The printer and the instruments were placed in a controlled room (10m x 5m x 3m) with no air circulation. During their testing, at the peak of the emission, the particulate concentration was measured as 900 micrograms/m^3. In the same study, they also showed that nanofiber filters are capable of capturing $PM_{2.5}$ particles. Kwon, Yoon, Ham, Park, Lee, Yoo, and Kim (2017) analyzed the emissions and control methods of nanoparticles during the FDM printing process. The tests were performed in a 2.5m^3 test chamber with PLA, HIPS, Nylon, PVA, laywood, and ABS materials. For each type of material, the manufacturer-recommended temperature settings were used. Particle emission rates and concentrations were measured for particle sizes from 10 nm to 10000 nm. At these conditions, the highest emission rate was recorded for HIPS ($5.75x10^{11}$ particle/min) and nylon ($4.34x\ 10^{11}$particle/min). ABS had an emission rate of $8.85x10^{10}$ particle/min. PVA and PLA had minimum emission rates of $1.23x10^{9}$ particle/min and $7.92\ x\ 10^{8}$ particle/min, respectively. The researchers also recommended various methods for reducing the emission of nanoparticles. Using high-efficiency particulate air filters (HEPA) with enclosure was recommended for high-emitting materials. For open-structure designs, low-emitting materials or applying low temperatures to prevent combustion and carbonization of organic compounds in plastics printing materials was recommended.

In another study, Floyd, Wang, and Regens (2017) measured aerosols and VOC emissions. The test was performed in a 24.8L controlled testing chamber. Eight different filament materials (ABS, PLA, PVA, HIPS, PCABS, nylon, bronze-PLA, and PET) were studied at the same nozzle and baseplate temperatures of 210°C and 70°C, respectively. Testing was done for particles ranging from 16.8 nm to 532.8nm. For that range, ABS had $3.2x10^{11}$ particle/min and PLA had $0.8x10^{11}$ particle/min emission rates. VOC emissions of ABS and PLA were measured as 63.9 μg/min and 50.1 μg/min, respectively. Researchers identified the top three emitted VOC species by weight percentage for each printing material. Styrene was found in ABS, HIPS, and PCABS printing samples and acrylic acid dimer was found in PLA and bronze-PLA printing samples.

Another FDM study was conducted by Zhou, Kong, Chen, and Cao (2015) in a 60 m^3 ten-thousand-level clean room. The research was performed on the particle emission from ABS plastic for particle size ranging from 0.25 µm to 32 µm. In that range, the highest emission concentration was recorded for particles with sizes of 0.25-0.28 µm at 5x104 particle/L. It is noteworthy that the concentration of particles from 0.375 µm to 32 µm was at negligible levels. Deng, Cao, Chen, and Guo (2016) also studied FDM with ABS and PLA. The test was done in an 8m^3 cleanroom for particles ranging from 2.5 nm to 20 nm. They divided the printing process into four stages and showed that the maximum emission occurred during the heating stage, and the emission rate increased with an increase in temperature. They could not find any significant influence of feed rate. At their highest levels, emissions from ABS was 20,000 particle/cm^3, and PLA was 40,000 particle/cm^3.

Azimi, Zhao, Pouzet, Crain, and Stephens (2016) measured ultrafine (particles smaller than 100 nm) particle and VOC emissions using a 3.6m^3 test chamber for nine different filament materials (ABS, PLA, HIPS, nylon, laybrick, laywood, polycarbonate, PCTPE, and T-Glase). For ultrafine particle emissions, they observed the highest emission rates for ABS filaments ranging from $2x10^{10}$ to $9x10^{10}$ particles/min. Parallel with other studies, styrene (a known carcinogenic VOC) was measured to be the most-emitted VOC when ABS and HIPS filaments were used for printing. The highest-emitted VOC from the PLA printing process was found to be lactide, which is the monomer of PLA plastics. Whereas, caprolactam was the primary VOC measured during the printing of nylon, PCTPE, laybrick, and laywood. Both styrene and caprolactam levels were significantly above recommended or normal levels.

Aguilera (2016) found that, for FDM processes, part design and build pathing had significant effects on emission rate. It was reported that long nozzle travel time without printing increases particle emissions. Many other researchers (Zhang, Wong, Davis, Black, & Weber, 2017; Gu, Wensing, Uhde, & Salthammer, 2019; Mendes et al., 2017; Steinle, 2016; Yi et al., 2016; Azimi et al., 2016; Kim, Yoon, Ham, Park, Kim, Kwon, & Tsai, 2015; Floyd et al., 2017; Stefaniak et al., 2019; Zhang, Sharma, Wong, Davis, Black, Biswas, & Weber, 2018; Zhou et al., 2015; Wojtyła, Klama, & Baran, 2017; Azimi, Fazli, & Stephens, 2017; Deng et al., 2016; Bharti & Singh, 2017; Stephens et al., 2013) studied emissions from FDM processes and found parallel results to the aforementioned studies.

Binder Jetting

The binder jetting process was studied by Afshar-Mohajer, Wu, Ladun, Rajon, and Huang (2015). Their research focused on the emission of total suspended particles (TSP), ultrafine and submicron particles (10.4-407 nm), super micron particles (0.45-20 µm) and TVOCs. They found that $PM_{2.5}$, PM_{10}, and TVOC emissions exceeded USEPA ambient-air quality standards.

Laser Sintering

Damanhuri, Fauadi, Hariri, Alkahari, and Omar (2019) researched laser sintering with polyamide nylon powder. They measured TVOC levels at 1.7 ppm and formaldehyde levels at 0.05 ppm, which are at acceptable levels.

Stereolithography

Yang and Li (2018) studied the stereolithography 3D process and found TVOC emission levels to be significantly higher than the recommended levels.

Metal 3D Printing

Graff, Ståhlbom, Nordenberg, Graichen, Johansson, and Karlsson (2017) and Mellin, Jönsson, Åkermo, Fernberg, Nordenberg, Brodin, and Strondl (2016) measured particle emissions during selective laser melting (SLM) of Inconel 939 alloy for particle sizes ranging from 10 nm to 10 µm. Inconel 939 alloy contains high amounts of chromium, cobalt, and nickel. They measured low levels of emissions for particles smaller than 300 nm. However, the emission levels of particles from 300 nm to 10 µm indicates a potential health risk requiring further research. Du Preez, De Beer, and Du Plessis (2018) studied the shape and size of metal powder particles from three different titanium alloys used for metal 3D printing. In one sample, 10% of the particles were smaller than 11 µm, and in all three samples, they found a significant number of particles smaller than 4µm. They also mentioned that the existence of such small particles was not consistent with the material safety data sheets provided by manufacturers. Long-term exposure to these materials carries a potential health risk.

Bau, Rousset, Payet, and Keller (2019) studied the selective laser melting of stainless steel (316L). The results indicated high emission rates of 50-100 nm chromium (CrVI) particles. Most of the metal used in 3D printing processes are in the form of fine powder. Of those powders, titanium and iron inhalation may lead to respiratory irritation, including coughing and sneezing (Adams, 2006). Long-term inhalation of aluminum dust may lead to pulmonary fibrosis (Tokar, Boyd, Freedman, & Waalkes, 2013).

Research on Lab Subjects

FDM with ABS plastic and stereolithography (STL) with photocurable liquid resin are two AM technologies that require post-printing cleaning. Oskui, Diamante, Liao, Shi, Gan, Schlenk, and Grover (2015) analyzed the toxicity of 3D-printed parts from these two AM technologies after cleaning the sample parts according to the manufacturer

recommended procedures. Their research showed that parts from both AM technologies are "measurably toxic" to zebrafish embryos.

Robust systemic microvascular dysfunction after inhalation of fine particulate matter and nanoparticles was also reported before similar studies were performed on 3D printers (Nurkiewicz, Porter, Barger, Castranova, & Boegehold, 2004; Nurkiewicz et al., 2006; Nurkiewicz, Porter, Hubbs, Cumpston, Chen, Frazer, & Castranova, 2008; Nurkiewicz, 2009). Other experiments (Jani, Halbert, Langridge, & Florence, 1990) showed that when 50 nm polystyrene particles were administered to rats, these smaller particles were distributed to the liver, spleen, and bone marrow, whereas particles >100 nm did not reach bone marrow, and particles >300 nm were not detected in the blood. Recently, Stefaniak, LeBouf, Duling, Yi, Abukabda, McBride, and Nurkiewicz (2017) observed mice while 3D printing ABS-based parts. They reported that main arterial pressure (MAP) was significantly elevated after exposures, and systemic microvascular dysfunction was also observed.

Surveys

Chan, House, Kudla, Lipszyc, Rajaram, and Tarlo (2018) surveyed 47 employees from 17 3D-printing facilities (seven commercial rapid-prototyping businesses, seven educational institute—colleges and universities—and three public libraries). Of the survey participants, 59% stated that they had "experienced respiratory symptoms more than once per week in the past year." Researchers studied the participants in three categories according to their work hours per week with 3D printers: less than 20 hours, 20-40 hours, and more than 40 hours. They showed that "having a previous respiratory diagnosis, including asthma or allergic rhinitis, was significantly associated with working more than 40 hours per week with 3D printers."

Reported Cases

A case of asthma was reported by House, Rajaram, and Tarlo (2017). An adult worker with a history of childhood asthma redeveloped asthma symptoms after being exposed to 3D printing of ABS plastic parts in a 3000-cf^3 room with ten 3D printers. A case of hypersensitivity pneumonitis (HP), which is typically associated with being exposed to short nylon fibers in the textile industry, was reported by Johannes, Rezayat, Wallace, and Lynch (2016). In this case, the HP was found to be "attributed to inhaled nylon powder" used in selective laser sintering 3D printing. Creytens, Gilissen, Huygens, and Goossens (2017) reported two cases of allergic contact dermatitis.

Discussion

Occupational safety and health is gaining more attention from researchers, as society is becoming more concerned about workplace hygiene. With advancements in material science, particularly in nanomaterials, nanomaterials and nanomaterial-based products have become more prevalent in our daily lives. Beside its advantageous material characteristics, nanomaterials carry potential health risks and challenges with its production, handling, transportation, use, and disposal in manufacturing environments, school labs, office areas, and our homes (House et al., 2017; Deng et al., 2016). Analysis and monitoring of nanoparticle emissions to air, water, and soil is a fundamental research subject mainly in new materials and advanced manufacturing areas. The majority of the literature available for this research study was concentrated on the study of particle emissions to air. For this purpose, researchers measured emission rates of UFPs, TVOCs, and specific VOCs under various conditions for different materials. Of those materials measured, PLA and ABS were the most commonly studied materials, as they account for more than half of all plastic 3D printing materials consumed in the world (Yang & Li, 2018). However, there is no standard for the composition of PLA and ABS plastics used by 3D printing technologies, their compositions, and, hence, their emissions differ significantly depending on the materials' manufacturer. Many details about the composition of 3D printing-emitted particles still remain unknown.

In terms of UFP emissions, PLA is regarded as considerably safer than ABS. According to many reports, UFP emission of PLA is close to room background UFP concentrations. PLA's chemical structure is also safer because of its biocompatibility. On the other hand, ABS was observed to have 10 to 1000 times higher UFP emission rates compared to PLA. It is known that UFP can enter the lungs and bloodstream through inhalation. However, there are no exposure standards set for UFP concentrations based on health criteria, which makes it difficult to develop recommendations for exposure limits. Underwriters Laboratories (2019) recently developed and published a standard method on testing and assessing particle and chemical emissions from 3D printers. The standard is intended for the assessment of a single 3D printer operating in a classroom/lab, home, or office setting. The UL standard for UFP is a performance-based standard that can be applied to a single printer in a controlled testing chamber for particles from 10 nm to 5 μm in diametric size. Of the 24 publications that looked at emission testing, only nine were conducted in a testing chamber. However, the measurement range varied significantly between the studies. Table 1 lists the findings from those studies for ABS and PLA plastic materials because of their popularity in 3D printing processes. Figures 1 and 2 provide graphical representations with the $3x10^{11}$ particles/minute benchmark reference line.

As for the TVOC emissions, the UL standard (UL, 2019) for the adopted AgBB's (German Committee for Health-related Evaluation of Building Products) recommendation has a set maximum allowable limit of 173 μg/min. Specific analysis of VOCs concentrates on emissions from PLA and

Table 1. Particle emission rates measured in test chambers.

Study ID number	Reference study	Measurement range (nm)	Emission rates of particles from ABS printing (# of particles/minute)	Emission rates of particles from PLA printing (# of particles/minute)
1	Vance et al. (2017)	14.6 – 680	1.08×10^{11}	1.25×10^{10}
2	Kwon et al. (2017)	10 – 1000	8.85×10^{10}	7.92×10^{8}
3	Floyd et al. (2017)	16.8 – 532.8	3.2×10^{11}	0.8×10^{11}
4	Azimi et al. (2016)	< 100	9×10^{10}	1.0×10^{8}
5	Gu et al. (2019)	5.6 – 10000	1.3×10^{11}	NA
6	Mendes et al. (2017)	1 – 350	6.24×10^{11}	1.0×10^{7}
7	Steinle (2016)	7 – 20000	2.4×10^{8}	2.1×10^{9}
8	Yi et al. (2016)	14.6 – 660	2.27×10^{11}	2.18×10^{11}
9	Kim et al. (2015)	10 – 420	1.61×10^{10}	4.89×10^{8}

ABS plastics. PLA has two primary ingredients that were detected by most studies: lactide and methyl-acrylate. Lactide is not considered to be toxic or hazardous. Methyl-acrylate can be hazardous if the concentrations surpass 265 mg/m^3; however, average measured concentrations for PLA-based 3D printing operations were found to be around 20 µg/m^3. In contrast, primarily detected VOC during ABS-based printing operations was styrene. Styrene is a known carcinogen that also causes nausea, dizziness, and headaches. The maximum exposure limit set for styrene by OSHA is 426 mg/m3 for eight hours. The American Society of Heating, Refrigerating, and Air Conditioning Engineers (ASHRAE) set an allowable limit for residential places at 87 µg/min. Azimi et al. (2016) measured 54.2 µg/min emission rates. At this rate, in a poorly ventilated room, it can potentially be harmful. In the literature, only five studies measured TVOC and styrene emission rates in a test chamber. Table 2 summarizes the TVOC and styrene emission rates measured in a test chamber, as described by the UL standard (UL, 2019). Figures 3-5 present emission data in a graphical form with the allowable limits marked.

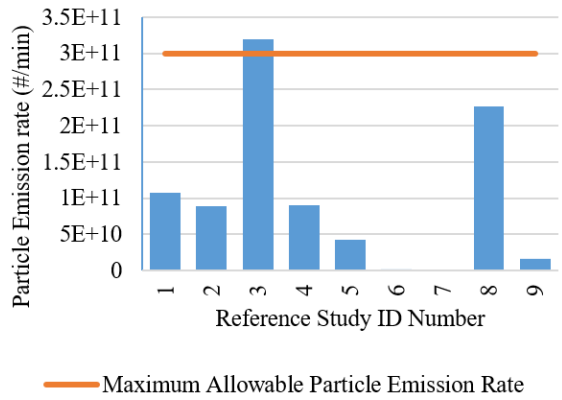

Figure 1. Particle emission rate from ABS.

Exposure to UFPs and VOCs depends on the distance between the operator and the 3D printer. In industrial applications, local exhaust ventilation systems, snorkel fume extractors, and enclosed ventilated racks are common technologies used for mitigating particle emissions. To reduce

Table 2. TVOC and styrene emission rates measured in test chambers.

Reference Study ID	Reference Study	Emissions rates of TVOCs from ABS printing (µg/min)	Emissions rates of TVOCs from PLA printing (µg/min)	Emissions rates of Styrene from ABS printing (µg/min)
A	Floyd et al. (2017)	63.9	50.1	21.2
B	Azimi et al. (2016)	68.4	17.3	54.2
C	Gu et al. (2019)	15	Not measured	6.4
D	Mendes et al. (2017)	Not different than background values	12	
E	Steinle (2016)	10	16	5.8
	Maximum allowable emission rates	173 (Source: ASHRAE 189.1)	173 (Source: ASHRAE 189.1)	87 (Source: AgBB)

the effects of emissions in non-industrial settings, most researchers recommended printing in a "big, well-ventilated" room. However, in those studies, the recommended room size or air change rate was not provided. Another commonly recommended practice was using manufacturer-provided enclosures and covers. On the other hand, Afshar-Mohajer et al. (2015) showed that this method kept the particles inside the enclosure during the printing activity, but particles were released when the door or cover was opened to remove the printed parts. Azimi et al. (2017) tested different mitigation scenarios and reported that "high-flow spot ventilation systems" and "sealed enclosure with high-efficiency gas and particle filtrations (Photocatalytic filter)" are the two most effective methods for eliminating 95% to 100% of UFP and TVOC emissions. It was also advised to use high-quality materials with low emissions, such as PLA. Although some researchers recommended using high-efficiency particulate air (HEPA) filters, those filters are not capable of capturing particles smaller than 300 nm.

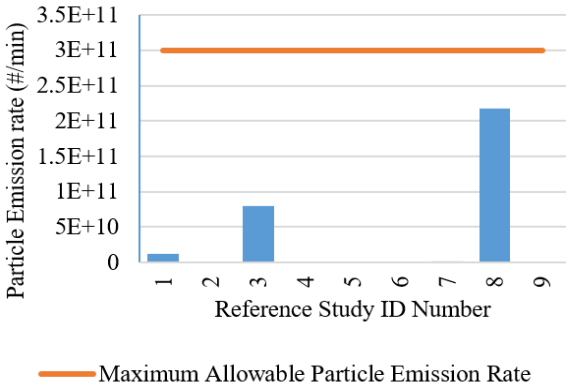

Figure 2. Particle emission rate from PLA.

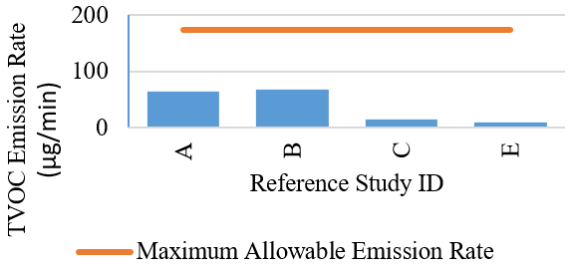

Figure 3. TVOC emission rate from ABS.

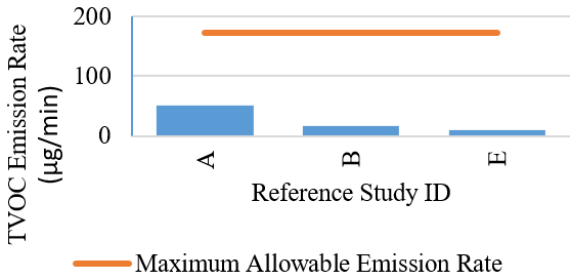

Figure 4. TVOC emission rate from PLA.

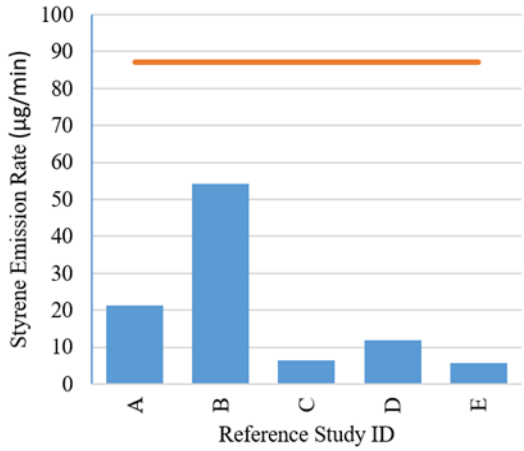

Figure 5. Styrene emission rate from ABS.

Conclusions

Previous research has raised concerns about the particulate matter and VOC emissions of plastic-based printing materials. More research is needed for different AM technologies and different printing materials. Since AM technologies are not only used in manufacturing settings but also schools, homes, and garages, more research is needed to understand the potential health risks of AM technologies.

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Biography

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Bridging over Criminal Justice to Address the Growing Threats of Nanotechnology in Local Communities: An Introspective Look At How Nanotechnology Is Impacting First Responders

David M. Scott, University of Texas at Tyler; Dominick Fazarro, University of Texas at Tyler

Abstract

The demand and increase for nanotechnology and nano-based industries have grown exponentially over the past forty years. Both medical and commercial product manufacturers are continually seeking the next generation of nano-based materials. Furthermore, these same materials are also sought after by terrorist and extremist groups whose motive is to inflict destruction, death, and chaos against enemy states. As this reality evolves with each passing day, it is becoming apparent that, should a nano-based attack or nano-based war were to occur beginning at the local level, law enforcement and first responders lack adequate training and understanding in their mainstream of training about nanotechnology and how those agents could be potentially weaponized. The purpose of this current study was to review the existing body of knowledge and present a working definition of nanotechnology, the supply and demand for nanotechnology globally, the weaponizing of nanotechnology, and the fallout of a nuclear nano-based attack. In this paper, then, the authors wanted to provide a scenario of how a potential attack would theoretically begin in a local community and describe the challenges first responders would face in such a crisis before it had a chance to spread.

Introduction

Local law enforcement communities, since their inception in America, have struggled to keep up with our ever-changing world. This is especially true in the technological world. For the past two decades, cybercrimes, such as child pornography, identity theft, and human trafficking, have inundated curricula for ongoing and required training in basic police academies. As police officials and policy makers attempt to remain abreast of the dynamics of our technological world, one area that has been rapidly advancing with little attention to first responders has been in nanotechnology; more specifically, the threat of a nano-war or nano-related attacks. Nano-war is the next evolution of both international and domestic crime and terrorism. What does this new theater look like? Very small or even invisible sensors and robots, developed for the military, could be used by state and non-state actors to invade privacy, such as nanotechnology-based biological agents, micro-robots, and sophisticated weapons (Altmann & Gubrud, 2004). Diseases such as malaria, severe acute respiratory syndrome (SARS), and coronaviruses are able to be weaponized. A small outbreak in a centralized area could create a pandemic in a matter of weeks.

How would local or state law enforcement agents combat this? Since the 9/11 attacks on America, local law enforcement and first responders have had training in responding to weapons of mass destruction (WMD). Large-scale attacks, such as an airline striking a building or the detonation of a dirty bomb in a public area, have been the themes. An event such as a nano terror attack or an industrial accident involving nanomaterials being released into the air or water supply is quite different. There would be no immediate response by law enforcement until individuals starting to display symptoms of whatever nano-based agent was released. This could mean that days or weeks pass and the nano infection spreads to pandemic levels. In this paper, the authors address the ever-developing and growing threat of nanotechnology that could potentially be used to threaten the welfare and stability of local communities. The growing threats, both unintentional and intentional, mandate that first responders gain a working knowledge of our nanotechnological world in future police training. This perspective illustrates the dangers that may occur in the production of nanotechnology for legitimate products and the danger of weaponizing those same products to cause the harm or death of individuals.

Breaking down Nanotechnology

Nano is a prefix meaning "billionth" ($1x10^{-9}$ or 0.000000001) derived from the Greek word *vavos*, meaning "dwarf" (Leins, 2017). Gsponer (2008) defines it this way: "Nanotechnology, the science of designing microscopic structures in which the materials and their relations are machined and controlled atom-by-atom, holds the promise of numerous applications." Vandermolen (2006) defined nanotechnology as, "the manipulation and control of matter at the scale of the nanometer (one-billionth of a meter)—roughly the diameter of a small molecule." In another study, Lein (2017) reported that, "nano-sized materials are impossible to see with the naked eye and are difficult to contain, and are easy to aerosolize, particularly with current technology." Kosal (2010) added that, "Nanotechnology is not a discrete technology rather, in dealing with matter at the molecular scale, it spans the fields of physics, biology, and chemistry, and it blurs boundaries between electrical engi-

neering and biomedical engineering and virtually all the disciplines in between." This discipline also includes the field of criminal justice and criminal forensics.

According to the Centers for Disease Control and Prevention (CDC) in the US, "there have been 17 confirmed anthrax infections in which the delivery of anthrax was not natural but rather weaponized" (Anthrax, 2001). Today, with nanotechnology, small microbes like ricin or microbe subunits of anthrax could be encapsulated for an easy delivery system (Kosal, 2010). Kosal further reported that, "Nano-carrier and encapsulation technologies have already been developed in the pharmaceutical industry for the efficient and targeted delivery of drugs and image contrast agents and are increasingly used in the cosmetics, agriculture, food, paint, and other material applications." Such products in both medicine and produced commercially have risen dramatically in recent years from quantities of grams to tons (Kosal, 2010).

Supply and Demand for Nanotechnology

World Powers such as China, Mexico, Russia, Israel, and even the US have been experimenting with nanotechnology that could be used as weapons of mass destruction. But instead of focusing on nuclear annihilation and leaving the world uninhabitable, these super powers are focusing on nano-level warfare. Aside from the global superpowers Kosal (2010) reported that, "other countries are also in pursuit of nanotechnology such as Japan, Taiwan, India, Iran, and across Europe." Gao, Biyu, Weiyu, Sinko, Xie, Zhang, and Jia (2016) stated, "currently there are more than 60 countries that have launched national nanotechnology programs." In 2004, Altmann and Gubrud (2004) stated that "The United States of America accounts for two-thirds of the global expenditures for military research and development (R&D) ($52 billion in 2002), followed by France and the U.K. with a combined $7 billion, then Russia and China, combined about $3 billion." By 2015, the US federal budget alone had provided more than $1.5 billion for U.S. governmental research and development initiatives involving nanotechnology-related activities of 20 departments and independent agencies including academia, government, and industry laboratories (Leins, 2017). By 2020, nanotechnology will reach spending limits of three trillion dollars to develop products in the consumer and commercial sectors (Del Monte, 2017). Ironically, as this sector has grown, there has not been any increased training for first responders on just what nanotechnology is, the potential threats associated with it, and strategies to combat a nano-based accident or attack in local communities.

The Ecological Damage of Nanotechnology in Local Communities

As it is evident that more nations are seeking or embracing a nanotechnological foothold in the world, there are safety concerns that are paramount for local first responders. The production of nanotechnology materials or target compounds are combinations of both dangerous and highly lethal ingredients. Nasu and Faunce (2012) stated that, "currently there is very limited information available on the potential persistence of nanoparticles in the environment, and the presence or removal of nanoparticles during various waste treatment processes, particularly in relation to weathered nanoparticles that have undergone agglomeration and transformation." The same binding properties that deliver therapeutics to cancer cells might also deliver toxic substances to aquatic organisms, if similar materials are released or used in the ambient environment (Balbus, Florini, Denison, & Walsh, 2006).

According to Balbus et al. (2006), "the federal agencies are unlikely to be able to put into place adequate provisions for nanomaterials quickly enough to address the products now entering or poised to enter the market." The "voluntary standard of care for nanomaterials must play a role in guiding the safe use of nanomaterials in the meantime" (Balbus et al., 2006). This would indicate that local agencies that have a nanotechnological production site or facility lack oversight to ensure the safety and wellbeing of the surrounding community. The result is that if a release of chemicals or an explosion were to occur, local law enforcement and first responders would activate to immediately deal with the emergency. Therefore, training in the use of nanomaterials and their properties is critical. Personal protection equipment (PPE) would have to be purchased and distributed, and personnel would have to be trained on how to appropriately don the gear when responding to a nano-based critical incident.

The paradigm of a nuclear war has shifted from a zero-sum game, to a focus on avoiding the destruction of an enemy, to now using nanotechnological weaponry that would leave existing infrastructure intact, while annihilating local inhabitants. Theoretically, with the pursuit of nanotechnology, the deep-rooted pursuit of obtaining or creating a nuclear weapon, biological weapon, or a chemical agent or weapon of mass destruction could be easily fabricated or sold on the illegal market. For example, extremists using nanotechnology developed to deliver cancer-curing drugs or treatments to patients with botulism, cholera, SARS, malaria, or even the plague could be manipulated to be used by terrorists or terrorist-sponsored states to spread diseases throughout a population.

According to Savron (2010), nanotech "insects" could potentially be used to inject and infect humans on a mass scale with specific precision and, "that unlike nuclear weapons, there would not be a need to have huge factories to accomplish this, nor would smuggling nanotech weapons into an unsuspecting region be difficult for a terrorist or extremist with little or no formal training on how to intercept or prepare for a nano type fall out." With that being theorized, the fear of a nuclear fallout or nuclear winter

would no longer be a concern for terrorists or terrorist-sponsored states. With nanotechnology, weapons could be hyper-targeted, thus causing low collateral damage. Governments would be more interested in using nanotech weapons to avoid a full nuclear winter in order to maintain the infrastructure of targeted nations and cities. In terms of local law enforcement, these threats should also be applied to domestic terrorism or domestic extremist groups operating within the US, such as the Klu Klux Klan, the Crips, the Phineas Priesthood, and the Earth Liberation Front ("The Elves").

Weaponizing Nanotechnology

The forces of technological and economic globalization that have dramatically altered the international business environment are radically reshaping the nature of the nuclear and biological threats the world faces (Luongo & Williams, 2007). As new technologies evolve, the intent of the good use of technology seems to be short lived by people who use the same technology as an advantage to inflict harm on society. This has been termed DURC, or dual use research of concern (Leins, 2017). Leins went on to write, "DURC occurs when a particular capability, such as nanotechnology, might be beneficial or also could potentially be damaging and destructive; for example, mimicking pathogens." Another theory is nanotechnology being created to target drug delivery. Kosal (2010) supported this claim by writing, "this has been commercially available for a few years and could be manipulated in the creation of new chemical or biological threats."

However, Vandermolen (2006) erred on the side of caution by stating, "the dangers posed by molecular nanotechnology (MNT) are also nearly limitless: cheap, fast, mass production would enable spasmodic arms races, and improved smart materials could make current weapons systems much more capable, permitting the creation of an entirely new class of weapons." Furthermore, Kosal (2010) stated that, "communication of those new discoveries is occurring faster than ever, meaning the unique ownership of a piece of technology is all but impossible." Vandermolen (2006) stated that, "the aspiring arms producer would have to provide only designs, power, and basic materials" thus creating the term "Nano-hackers."

Individuals hacking computer servers for fun or with malicious intent will eventually move to hacking into nanotechnology-based products that include gene therapies, machinery, and weaponry designed for defense purposes. Such information could be traded or sold on the dark web to radical groups or terrorists. The decisions in the last 72 years since the fission of the atom have been a distraction, first with the dropping of two atomic bombs over Japan and second in the use of the nuclear energy to power cities. The increase of trillions of dollars may indicate an aggressive posture to develop nano-weapons. There are nearly unlimited applications for nanotechnology in the military sector. Weapons such as mini-nuclear bombs, insect lethal robots, and nano-bioweapons/toxic nanoparticles. The development of such weapons is a real global threat and could be the next generation of weapons of mass destruction (Del Monte, 2017). Furthermore, these types of weapons can introduce a new era of terrorism by 2030. Recently at the Cambridge University Conference on Global Catastrophic Risk theorists proposed that there is a five percent risk that nano-weapons could cause the extinction of the human race by 2100 (Daniels, 2017).

Nuclear Fallout and How a Nano-Nuclear Technological Attack Would Be Different Today

Twenty-five years ago, international teams of scientists showed that a nuclear war between the US and the Soviet Union could produce a "nuclear winter" in which the smoke and fires started by the bombs would envelop the planet and absorb so much sunlight that the earth's surface would get cold, dark, and dry, killing plants worldwide and eliminating the food supply (Robock & Toon, 2009). It was theorized that, "a full exchange, thousands of such clouds, produced by individual explosions and merging with one another, could blanket northern mid-latitudes in days, altering the atmospheric radiation balance and eventually perturbing the circulation and climate on a global scale" (Turco, Toon, Ackerman, Pollack, & Sagan, 1983). To explain this theory, Robock and Toon (2009) conducted simulation models of Pakistan and India engaging in a nuclear war with one another and examined the global consequences. In their research these researchers theorized that, "after calculating wind that the entire globe would be engulfed in black smoke from the war within two weeks." Furthermore, "the black smoke would absorb the earth's sunlight and increase the temperature in the stratosphere, eliminating any chance of rain purifying the air quality."

Interestingly, Toon, Robock, and Turco (2008) conducted the same simulations and predicted that, "the soot from the nuclear fires from a regional conflict, like India and Pakistan for example, would be sufficient to produce the lowest temperatures the Earth has experienced in the past 1000 years—lower than during the post-medieval Little Ice Age or in 1816, the so-called year without a summer." Those authors concluded that, "the temperature changes would have a profound effect on mid- and high-latitude agriculture, specifically tropical areas like South America and Africa would experience a large diminution of rainfall from convection in the rising branch of the Hadley circulation, the major global meridional wind system connecting the tropics and subtropics (Toon et al., 2008). In addition, Robock and Toon (2009) made predictions that such a small event would also keep volcanic particles in the air for at least two years after the incident, while the smoke from the nuclear fires would remain at least a decade. The absence of sunlight would have an immediate effect on the planet, reducing global temperatures and having a direct impact on

food sources such as vegetation and wildlife, with a prediction that world food supplies would run out in two months (Robock & Toon, 2009).

That was yesterday with a nuclear fallout. Today, with nanotechnology being weaponized and virtually undetectable, unlike an intercontinental ballistic missile (ICBM) destroying a region of the globe, weaponized nanotechnology would have more precise consequences. To put the nanotech threat into context, the delivery of such destruction used in society would be virtually undetected and untraceable until the impact had already commenced. A simulation or a scenario of a nanotech-type attack in a metropolitan area the size of Dallas or Chicago would be catastrophic. There would be no ground zero or point of entry of an attack for this type of event. The scenario of a microscopic delivery of an unknown illness, pathogen, or virus infiltrating a city would immediately overwhelm local law enforcement.

A delivery system such as an airplane, bus, or even a sporting event could start a local catastrophic event that could quickly spread globally. Initial reports of such an event would cause a mass panic. The 911 call centers would be overloaded with emergency calls. Hospitals and clinics would be flooded with patients presenting symptoms with untraceable origins. Once capacity has exceeded the resources at local medical facilities, diversion protocols would activate, possibly spreading a nano-attack to other facilities not yet infected. The idea of containment would then be moot. Simultaneously, schools and local government resources would shut down and possible riots and other civil unrest would begin. This sequence of events would initiate a disintegration of social structure as the spread expanded to other cities. Local law enforcement would have to begin to triage how to contain the attack, while attempting to sustain public order within their jurisdiction. This is just the beginning or micro event. The question of how such a small (nano-level) event in one local community would unfold if several cities underwent the same or similar events across the nation is unimaginable.

Conclusions

The reality of a nano-based terroristic attack is real, just as scientists predicted a coronavirus pandemic in 2017 that seemed implausible and which later occurred in 2020. It was not a matter of if, but when, such an event would occur. The concept of total nuclear annihilation of an enemy is being redefined. However, during this discovery of applying nano-sizing to emerging practices, problems are occurring. The first is the expansion of nanotechnology industries racing to keep up with the global competition of supply and demand. As the use of nanotechnology is already underway, more communities can expect to see the presence of this new industry with little or no oversight by the federal government. Industrial accidents in the production or transportation of dangerous nanoparticles is a major concern. Just as chemical spills occur, law enforcement will be expected to respond and deal with similar issues involving nanoparticles.

Second is the more malicious situation in which a community is attacked using a nanotech weapon. These attacks are virtually undetectable and untraceable for law enforcement. Most local departments currently have neither the equipment nor the capability to counteract this type of threat. Both threats require ongoing discussions and conversations about how to implement training for this science to local, state, and federal law enforcement officials. The need to develop memos of understanding (MOUs) on how critical information will be shared among various agency officials will be needed. The detailing of best practices to provide pertinent training for law enforcement and all levels and disciplines in communities will be needed. The reality is that law enforcement and local government agencies are not prepared to combat and triage a nano-based incident or attack if it occurs inside the US. Efforts to address and combat this risk require a complete paradigm shift from traditional methods and practices in law enforcement. More training and equipment will be needed in the future to keep first responders safe as well as to ensure safety and stability within communities.

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Novel Technique for Analyzing the Effects of Cognitive and Non-Cognitive Predictors of Student Course Withdrawal in College

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Abstract

In this study, the author applied a novel technique to a database of college students to identify the cognitive and non-cognitive factors that predict college students' course withdrawal behaviors. The author analyzed predictors such as high school grade point average (HSGPA), standardized test scores (ACT–American College Test or SAT-Scholastic Aptitude Test), number of credit hours enrolled in during the current semester, previous credit hours passed, college CGPA until current semester and number of hours withdrawn, gender, and age. Data mining software algorithms were used to study information about undergraduate students at a west-south-central state university in the US. The study results revealed that two factors, number of enrolled credit hours and a student's age, had the largest effect on collegiate course withdrawal behaviors, irrespective of HSGPA and standardized test scores. Other researchers have discovered similar results when they applied t-test, simple regression, multiple regression, and discriminant analysis tools. Lastly, the empirical analysis showed that the data mining technique outperformed alternatives. These techniques can be applied to similar studies on college student databases and can be a suitable instrument for administrators of the colleges.

Introduction

Each semester of an academic year, a substantial proportion of students withdraw partially or entirely from their courses. The major consequences of withdrawals include delaying graduation, lengthening the total time for education, and wasting university resources such as faculty underload, computing labs, library resources, and other support services. In this study, the author considered two scenarios: 1) it is in the students' best interest to complete a course if they have a higher chance of earning a final grade of 'D' or better, and 2) the student completed the course but earned an 'F', in which case withdrawal would have been a better decision. Some college administrators believe that course withdrawals are the result of the university failing to meet the needs of its students. Another view of this topic is the effect from students' financial or personal problems (Lucier, 2019). Overall, this is a complicated mix of cognitive and non-cognitive variables that cause students to drop courses within days of beginning them. Predicting student success is really a process of determining what group that individual feels is most appropriate. In general, a student's academic skill set and drive are the most important factors when avoiding withdrawal and doing well academically. The skill set may include self-belief, critical self-reflection, independent learning, self-management, social skills, dealing with stress, critical thinking, academic ability, and information literacy (McMurray, 2011; Moore, 2004; Morisano, Peterson, Shore, Hirsch, & Pihl, 2010; Muris, 2001; Schunk, 2003).

Cognitive traits such as persistence and motivation are also crucial. There are socioeconomic and health-related factors that can cause withdrawals, such as family crises, financial aid loss, personal or family illness, work schedule, inadequate internet access, and unanticipated job opportunities. In this study, the author assumed that such determinants could not be controlled by the students themselves and did not reflect on their academic prowess. The motivation of using data mining techniques to analyze information from a 10-year cohort of undergraduate students came from the inherent definition of the term. Data mining involves discovering new knowledge from databases. The findings may be unpredictable from the database. Also, there are no implicit assumptions that the underlying relationships between the predictors and the dependent variables are linear or nonlinear link functions or monotonic.

Previous studies indicated that standardized tests such as the American College Test (ACT) or the Scholastic Aptitude Test (SAT) were poor predictors of student success (Mirchandani, Lynch, & Hamilton, 2001; Carter, Bryant-Lukosius, DiCenso, Blythe, & Neville, 2014; Markert & Monke, 1990; Ebmeir & Schmulbach, 1989). In this current study, the author used seven additional variables along with test scores, as the database contained complete information of these factors. Additionally, literature was available on these factors as well, which enabled valid comparisons with findings of this work. These variables included age, gender, high school grade point average (HSGPA), credit hours taken (HRTK) during the current semester, previous credit hours passed (HRPS), college CGPA up until current semester, and number of hours withdrawn. Usually, studies with data sets similar to the one used in this current study use statistical techniques such as linear regression, multiple regression, and discriminant function analysis. Unfortunately, research utilizing data mining techniques to predict student course withdrawal behaviors is scant. Accordingly, two algorithms of data mining—the decision tree and association rule—were applied to this study.

Gadzella, Stephens, and Baloglu (2002) used linear regression analysis to study the effects of non-cognitive predictors, such as age, and cognitive predictors, such as learning style, on the academic performance of 105 students at a southwestern state university. The authors saw significant differences among age groups on course grades and withdrawal patterns. The oldest age group (34 to 57 years) performed the best and had the highest level of compliance in the study. Wolfe and Johnson (1995) used multiple regression analyses to identify SAT, HSGPA, and 32 personality factors to predict the college performance of 201 students at the State University of New York in Geneseo. They concluded that the following factors had the greatest effect: HSGPA (accounting for 19% of the variance), self-control (9%), and SAT (5%). It is notable that self-control was a function of age and number of attempted credit hours. Similarly, another researcher used multiple regression in a study of 505 freshmen at Portland State University to predict college performance with HSGPA, SAT scores, and age (Swiatek, 2007). That study revealed that non-traditional students aged 20-33 had a better perception about their courses and workload than traditional-age students of 19 and younger, considering how the former cohort had significantly lower HSGPA than the latter.

Kyoshaba (2009) used a Pearson products moment correlation statistical tool on survey data from a random sample of 340 undergraduate students at Uganda Christian University. There was a significant relationship between student HSGPA and standardized test scores with their academic performance. However, there was no relationship between the students' age and academic performance. Ting and Bryant (2001) used discriminant analysis to predict student retention at a southeastern comprehensive public university. Their analysis was a stepwise procedure that showed how acquired knowledge in a field was the only predictor for fall semester retention, whereas family influences and successful leadership experience were significant predictors for spring semester retention. Miller, Ryceka, and Fritsona (2011) adopted descriptive statistics, such as mean and standard deviation, and comparative statistics, such as an independent t-test (SPSS), on a student database. They found that high levels of classroom attendance and attentiveness increased a student's odds of remaining in a class.

In academia, student success has been one of the primary conversations on campuses across the world. Educational consideration, such as academic performance, is one of the most important attributes for student success. The earlier faculty or academic advisors identify students who are struggling academically, the better they are able to help those students get back on track before they are forced to withdraw from courses. That begs the question, which students are most likely to withdraw from their courses? And, what are the appropriate attributes for predicting student course withdrawal? The author developed this study in order to answer these questions. Additionally, the author aimed to create a robust and easy-to-understand data mining model for predicting student course withdrawal behaviors.

Materials and Methods

Many colleges collect more data than they actually need for an analysis. Some examples of information gathered include age, gender, birth year, high school location, high school GPA, high school graduation status, ACT and SAT scores, parents' education level, major, college GPA in each semester, withdrawal from courses in each semester, household size, parents' annual gross income, student's marital status, admission date, attempted hours, and number of remedial courses. In this current study, the author used data from 8208 students, who were in a ten-year cohort at a west-south-central state university of the US, and examined a set of eight attributes of each student. The data had adequate statistical power to analyze and derive predictions about the students.

In this study, the data from these 8208 students were partitioned into three groups, based on their major field of studies: 2156 students were science or engineering majors, 1232 students were non-declared majors, and 4820 students were non-science or non-engineering majors. The Records and Registration Department of the west-south-central university employed Oracle database software to store and process information generated from student records. In addition, it holds student enrollment and progress data. Structured query language (SQL) was used to extract data from the eight attributes for the 8208 students and transferred them into Excel files. In relational database management systems, SQL is used to communicate with a database. Thereafter, the data mining software imports data from these *Excel* files, which can them be mined by decision tree and association rules.

The author utilized a novel data mining technique to analyze information. There are numerous commercial or non-profit data mining software programs to choose from. For this study, the author used Waikato Environment for Knowledge Analysis (WEKA) (2018), a well-evaluated, openly available data mining software package. This application was adopted in order to accomplish this data mining study. WEKA is an assortment of computation algorithms for data mining activities and can either be functional to a dataset or called from programmer's own Java code. WEKA inherently uses several interfaces for pre-processing, classification, regression, clustering, association rules, and visualization of data, and is also well-matched for creating new computational schemes.

Data Mining Techniques

The author used two data mining algorithms, the decision tree and association rule. The association rule is effective for finding patterns of highly associated attributes. The deci-

sion tree is most effective for characterizing patterns of difference classes. Generally, the results from the decision tree, which are called decision rules, are easier to interpret than those from the association rule. However, due to its technical limitation, the decision tree may not always produce valid results for a skewed distribution.

Classification by Decision Tree

Data classification, which can be done in a controlled learning application, includes outcome rules or decision trees that screen the given data into predefined classes. For any representative problem in the realm of classification-rule learning, the conventional decision tree is very large is difficult to search exhaustively. In fact, the computational complexity of finding an optimal classification decision tree is NP hard (non-deterministic polynomial time hard). Figure 1 shows the basic steps of the decision tree algorithm (Han, Kamber, & Pei, 2011).

Input: The training *samples* are represented by discrete-valued attributes; the set of candidate attributes is the *attribute list*.
Output: A decision tree.
Steps:

(1) create a node *N*;
(2) **if** *samples* are all of the same class, *C* **then**
(3) return *N* as a leaf node labeled with the class *C*;
(4) **if** *attribute-list* is empty **then**
(5) return N as a leaf node labeled with the most common in *samples*; // majority voting
(6) select *test-attribute*, the attribute among *attribute-list* with the highest information gain;
(7) label node *N* with *test-attribute*;
(8) **for each** known value a_i of *test-attribute* // partition the samples
(9) grow a branch from node N for the condition *test -attribute* = a_i;
(10) let s_i be the set of *samples* in samples for which *test-attribute* = a_i; // a partition
(11) **if** s_i is empty **then**
(12) attach a leaf labeled with the most common class in *samples*;
(13) **else** attach the node returned by Generate decision test (s_i, *attribute-list-test-attribute*);

Figure 1. Decision tree algorithm.

Classification by Association Rule

An association rule suggests firm connotation associations among a group of objects (such as "happen together" or "one infers the other") in a database. A set of certain transactions, where each transaction is a set of literals (items), the association rule will find a countenance of the form X→Y, where X and Y are sets of items. The spontaneous sense of such a rule is that transactions of the database that contain X are inclined to hold Y. An example of an association rule can be: "35% of transactions that contain steak also contain sauce; 3% of all transactions have both of these items". Here, 35% is called the confidence of the rule, and 3% is the support of the rule. The delicate part of this procedure is to find all association rules that placate user-specified, least support, and least confidence limits. Figure 2 shows the pseudo code of the Apriori algorithm (Tang, Chuang, Hsi, Lin, Yang, & Chang, 2013).

```
Function apriori-gen (L_{k-1})
set C_k ← 0
for (all L_{k-1}.item_p, L_{k-1}.item_q ,L_{k-1}.item_p [i] =
    L_{k-1}.item_q [i], ∀i ∈ {1,…, k - 2})
c = {L_{k-1}.item_p [1],…, L_{k-1}.item_p [k - 2)], L_{k-1}.item_p
    [k -1], L_{k-1}.item_q [k -1]}
if (∀L_{k-1}.item ⊂c)
C_k ← C_k ∪c
end if
end for
end Function
```

Figure 2. Pseudo-code of the Apriori algorithm of association rules.

Results and Findings

The main goal of this study was to determine predictors for student course withdrawal behaviors. The author attempted to understand which groups of students were more likely to withdraw from one or multiple courses, because dropping classes was a potential indicator of academic performance. For example, the authors believed that a student withdrawing from multiple courses may indicate difficulty in keeping up with coursework. Students who have problems with class assignments and exams can get assistance from the university though services such as tutoring, counseling, advising, and mentoring. Generally, there are different withdrawal patterns from advanced courses based on a student's major. For instance, the degree of preparation in pre-college algebra or trigonometry can have a significant impact on an engineering student's withdrawal from differential calculus; however, this may not be the case for a liberal arts student. To identify the college performance patterns for different students, the author partitioned the students into three groups: students of science or engineering, non-declared majors, and non-science or non-engineering majors. There may be other ways to set student groups, but the author adopted this method for simplicity of handling the current database.

For each group of students, the experiment on withdrawal investigated the relationship between withdrawal and a set of selected cognitive and non-cognitive variables, including age, gender, major, HSGPA, SAT total score or ACT composite score, college CGPA, credit hours enrolled or taken

(HRTK), and withdrawn during any semester. The patterns obtained from this procedure can be used to predict freshman student performances. The university may also use these patterns to improve student recruitment and retention. For each experiment, if the decision tree algorithm had a valid result, the author only presented that result, as it was easy to understand; otherwise, the result from the association rule algorithm was presented. The thresholds for minimum support and confidence of the association rule algorithm were set to 0.05 and 0.7, respectively.

Students with Science or Engineering Majors

For this group of students, no valid result on withdrawal was generated from the decision tree algorithm. However, the association rule algorithm did generate a set of rules. Among them, two rules described patterns of withdrawal, while the rest described patterns of non-withdrawal. The following rules show the withdrawal pattern.

1. No students with 2 ≤ HSGPA< 3 and 12 ≤ HRTK<15 ever withdrew from a class.
2. No students with 18 <age ≤ 19, 12 ≤ HRTK<15, and 20≤ ACT score <20 ever withdrew from a class.

A specific observation in the data mining results showed that 66% of female students majoring in biology had at least one course withdrawal during the academic year. The overall finding of this group showed that only 17% of students majoring in science or engineering disciplines may have withdrawn in their entire college life.

Students with Non-Declared Majors

The contingency Table 1 shows that withdrawal is related to three categorical variables, HRTK, CGPA, and age, and reveals an interesting pattern. When taking between 9 and 15 credit hours, and with a CGPA greater than 3.0, a student is less likely to withdraw from enrolled classes (from 70% to 82% confidence).

Table 1. Withdrawal patterns of non-declared major students.

HRTK	CGPA	Age	Withdrawn	Confidence level
HRTK<=3	CGPA <2	age ≤ 19	No	84%
		20 ≤ age ≤ 39	Yes	70%
3< HRTK <=6	NS*	age ≥ 40	No	72%
6< HRTK <=9	CGPA ≥ 3	NS*	No	70%
9< HRTK <=12			No	77%
12< HRTK <=15			No	82%

* NS represents a statistically non-significant ($\alpha = 0.05$ and $p > 0.05$) value of the attribute found by data mining that had no influence on prediction.

The more credit hours taken by students with a high CGPA, irrespective of age, the more confidence they have in passing their classes. Moreover, non-declared students, who are older than 40 years and enrolled in one or two classes, usually do not withdraw (association rule's confidence level was 70%). Student registered for ≤ 3 credit hours with a CGPA ≤ 2.0 and between 20 and 39 years of age are 70% likely to withdraw from their courses. One way to explain this finding is that such students are unsure about their course of study or attending college in general.

Students with Non-Science and Non-Engineering Majors

Like Table 1, the contingency Table 2 demonstrates that course withdrawal is related to three categorical variables: HRTK, CGPA, and age. When taking 9-15 credit hours, and with a CGPA greater than 3.0, student are less likely to withdraw from classes (with 79% to 97% confidence). When enrolled in one or two classes, non-science and non-engineering majors with low CGPA ≤ 1.0 and ≤ 21 years of age are more likely to withdraw from course(s). It appears that this group is more vulnerable to dropping out of college and is in greater need of counseling and advising.

Evaluating Data Mining Results with ANOVA

The results shown in Tables 1 and 2 can be further evaluated using a statistical analysis of variance (ANOVA) technique. Association rule prediction showed that with withdrawal, the dependent variable was associated with three categorical independent variables: HRTK, CGPA and age. A three-way ANOVA determined a statistically significant relationship among HRTK, CGPA, age, and withdrawal $F(2, 8205) = 11.05$, $p < 0.001$, $\eta^2 = 0.50$. The strong point of this relationship, calculated by η^2, was solid for HRTK, which accounted for 50% of the variance in course withdrawal. From the results of the three student groups, the classifications by the decision tree can be summarized in a series of logical if-then conditions. The decision tree method of data mining does not require the implicit assumption that there are underlying relationships between the predictor variables and dependent variable, just like t-test, regression analysis, or descriptive statistics. In statistics, the generalized linear model generalizes linear regression by allowing the linear model to be related to the response (dependent) variable via a linear or non-linear link function and by allowing the magnitude of the variance of each measurement to be a function of its predicted value (Dalgaard, 2007). However, classification by the association rule method showed that all existing relationships in the database placate to a level of least support and least confidence constraints. The target of information finding is not pre-determined in association rule mining like it is with decision tree.

Table 2. Withdrawal patterns of non-science and non-engineering major students.

HRTK	CGPA	Age	Withdrawn	Confidence level
HRTK ≤ 3	CGPA<=1	18 ≤ age ≤ 21	Yes	72%
		22 ≤ age ≤ 24	No	67%
		25 ≤ age ≤ 29	No	81%
		age ≥ 35	No	83%
3< HRTK ≤ 6	CGPA ≥ 3	NS*	No	87%
6< HRTK ≤ 9			No	79%
9< HRTK ≤ 12			No	87%
12< HRTK ≤ 15			No	94%
HRTK>15			No	97%

* NS represents a statistically non-significant ($\alpha = 0.05$ and $p > 0.05$) value of the attribute found by data mining which had no influence on prediction.

Analysis of the study results showed that the most important attributes to academic performance are as follows: student academic factors (CGPA, HRTK) and cognitive attributes. Older (age>19) science or engineering majors with reasonable course loads (HRTK<15) had the lowest probability of course withdrawals. Course loads (HRTK), using number of credit hours as a metric, had a positive association with school withdrawal for both non-declared, non-science, and non-engineering major students. Academic advisors and counselors can apply the study's findings when planning course schedules that move students towards a simpler, easier route to graduation.

Student academic performance (CGPA) in the previous semester influenced whether they withdraw from courses in the current semester. For example, students with a high ratio of passed units to enrolled units in the previous semester were less likely to withdraw in the current semester. As expected, high numbers of failed or incomplete courses were associated with a higher risk of course withdrawal. Teaching evaluations and peer-to-peer faculty observations are the foremost tools for finding the root causes of these risky courses. Reorganizing the teaching pedagogy of these courses may overcome bottlenecks and save institutional resources.

Limitations of the Study

At this point, it is necessary to recognize certain limitations of this study. For example, there were other variables, such as parents' education, household size, wage earning, parents' annual gross income, marital status, dependency status, developmental courses required, that could have been studied. The authors perceived that analyzing the impact of these variables would have been useful, but faced limitations: 1) an extensive search showed virtually no studies that applied these additional variables; 2) the computation of the decision tree or association rule became NP (non-deterministic polynomial) hard in terms of required processing power by adding even a few extra variables. Inclusion of a mixed-method approach (data mining and statistical techniques) could be more interesting, which is the author's goal for future work.

Conclusions

In this paper, the author presented the application of a new technique for studying undergraduate student databases to identify course withdrawal behaviors. The students were divided into three groups, based on their major: science or engineering, non-declared majors, and non-science and non-engineering majors. Data mining often requires data preprocessing to ensure quality results. WEKA provided all of these functions. Findings of the study proved that the data mining algorithms of decision tree and association rule were well-matched for analyzing college student databases, because there is often little prior knowledge or a coherent set of theories or forecasts regarding which cognitive and non-cognitive variables (HSGPA, ACT/SAT, gender, or age, etc.) are related and how. It also demonstrated that the number of credit hours in which students were enrolled and age determined student course withdrawal features. Surprisingly, high school GPA and standardized test scores were not necessarily real signs. In general, then, researchers may conclude that the novel technique presented here can be a useful tool for college administrators to determine withdrawal patterns of the vast majority of their students, which eventually will save institutional resources. Additionally, administrators may be able to locate students vulnerable to withdrawal from classes, as so many students are on financial aid every year. Thereafter, faculty may put statements on their syllabi and be encouraged to talk with these students early on about the ramifications of withdrawing from their classes.

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Biography

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