Can artificial intelligence and fuzzy logic be integrated into virtual reality applications in mining?

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Synopsis

The University of New South Wales (UNSW Australia) has been a world leader in the development of innovative virtual reality technologies over the last 15 years. AVIE (Advanced Visualisation and Interactive Environment) was developed by iCinema as a collaborative venture between UNSW's Faculties of Engineering and the College of Fine Arts. This is the world's first 360°-surround, virtual reality (VR) stereo projection theatre system.

The School of Mining Engineering at UNSW Australia has developed 18 different virtual reality modules aimed at mine safety training and mining engineering education. These modules are being regularly used in both the mining industry and the university. The School of Mining Engineering is continuously involved in the development of different modules. Research is also currently being conducted on the implementation of other technologies into this environment. Artificial intelligence (AI) and fuzzy logic are tools that the authors would like to consider implementing in future module development. This paper will review current research in both these areas and consider options for applying these technologies.

Keywords
mining, virtual reality, artificial intelligence, fuzzy logic.

Introduction

The School of Mining Engineering at the University of New South Wales (UNSW) Australia has progressively built simulators for the mining industry in collaboration with the industry. A project was commenced in 1999 with seed funding from UNSW and Coal Services Pty Ltd. Subsequently, funding was provided from industry in 2002 through the Australian Coal Association Research Program (ACARP). A flat screen 'proof of concept' system was deployed at Newcastle Mines Rescue Station (NMRS) in Argenton, New South Wales (NSW), Australia.

Stothard *et al.* (2004) described the development, deployment, and implementation of a virtual reality (VR) simulation capability by the School to address the specific needs of the Australian coal mining industry. The simulation capability developed is a hybrid system designed to provide simulation technology to both large and small operators. The system was deployed at mine rescue stations in NSW and is currently in daily use for training in areas such as unaided self-escape, rib and roof stability, hazard awareness, and isolation. The objective is to simultaneously train groups of miners in an environment where they are exposed to high-resolution, 'one-to-one' scale visualization of the underground environment in which they will operate.

From an educator's point of view, the effects of simulation and role-playing on students '*involves the whole person - intellect, feeling and bodily senses – it tends to be experienced more deeply and remembered longer*' (Brookfield, 1990). According to Meyers and Jones (1993), students who use simulations are '*forced to think on their feet, question their own values and responses to situations, and consider new ways of thinking*'. The main objectives are to make trainees feel as though they are located in the mine and provide them with a fully immersive experience (Stothard *et al.*, 2008).

Furthermore, the School has been involved in UNSW's award-winning iCinema Advanced Visualisation and Interaction Environment (AVIE) project – a 3D 360-degree VR facility and iDOME (proprietary hardware / software platform developed by the iCinema Centre) (Hebblewhite *et al.*, 2013; Mitra and Saydam 2011; Saydam *et al.*, 2011). The School has constructed an AVIE and an iDOME (a 2D version of the AVIE), funded partly by a Federal Capital Development grant in 2007, for developing mine safety training simulations. Figure 1 shows the AVIE and iDOME facilities at the School of Mining Engineering.

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Figure 1—(a) AVIE and (b) iDOME at the School of Mining Engineering, UNSW Australia

Advances in computing power have enabled great progress in artificial intelligence (AI) and fuzzy logic. These technological breakthroughs can best be utilized with a greater awareness of this technology and what it can achieve. This study will investigate if there is any potential for integrating fuzzy logic and AI into the VR technology that is currently used at the School.

Mining-related virtual reality modules developed at UNSW

Apart from developing modules aimed at improving the health and safety standards for the mining industry, the School has also developed numerous modules using the same technology for improving teaching and learning for mining engineering education at UNSW Australia. These modules are used in majority of the courses in both undergraduate and postgraduate teaching. All the modules are capable of running in the AVIE at the School and also on a standalone PC. Some of these modules are currently being adapted to run on the Internet so that students can access them at their leisure (Mitra and Saydam, 2011). The following is a list of the various modules that have been or are currently being developed for both the industry and learning and teaching (Hebblewhite *et al.*, 2013; Mitra and Saydam 2011; Saydam *et al.*, 2011):

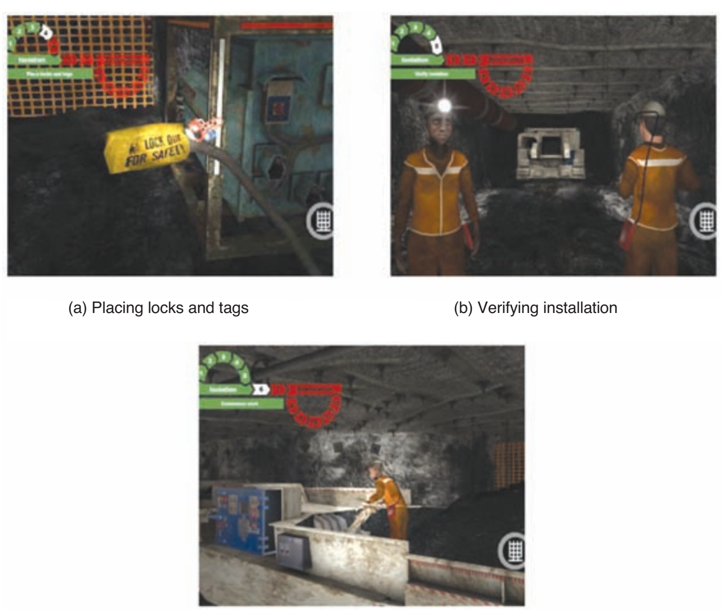
1. Hazard awareness
2. Isolation (Figure 2)
3. Outburst
4. Spontaneous combustion
5. Deputies inspection
6. Self-escape
7. Rib stability
8. Truck inspection (Figure 3)
9. Working at heights
10. Laboratory rock testing
11. Mining in a global environment (Figure 4)
12. Block caving (Figure 5)
13. Truck and shovel (Figure 6)
14. Longwall top coal caving (Figure 7)
15. ViMINE 1 (Figure 8) and ViMINE 2 (Figure 9)
16. NorthParkes community awareness
17. Coal geology (under development)
18. Caving geomechanics data visualization (under development).

Artificial intelligence

Artificial intelligence (AI) is defined as '*the study and design of intelligent agents where an intelligent agent is a system that perceives its environment and takes actions which maximizes its chances of success*'. This term was created by McCarthy (1956), and was defined as *the science and engineering of making intelligent machines* (ScienceDaily, 2014).

Russell and Norvig (1995) define four different categories for AI. These categories include systems that:

➤ Think like humans



(a) Placing locks and tags (b) Verifying installation

(c) Commencing work after completion of isolation

Figure 2—Screenshots from the Isolation module

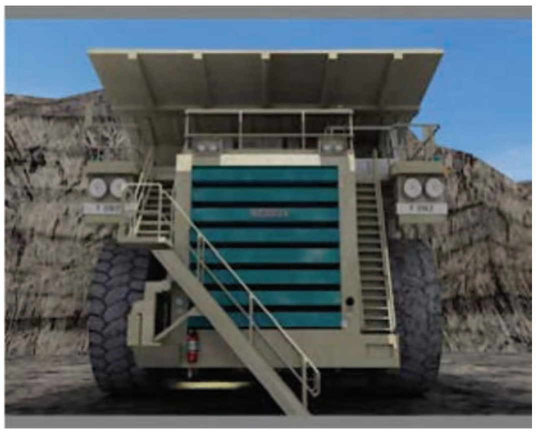


Figure 3—Screenshot of the truck used in the Truck Pre-shift Inspection module

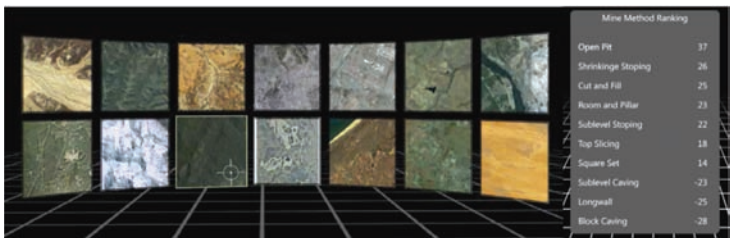
Figure 4—Students doing the assignment in the Mining in a Global Environment module

Figure 5—Drawpoint in the virtual block cave mine

Figure 6—Equipment selection simulation observed in the Truck and Shovel module

Figure 7—Screenshot from the Longwall Top Coal Caving module

Figure 9—ViMINE 2 open pit design



(a) (b)

Figure 8—ViMINE 1. (a) Selected terrain scenarios; (b) mining method ranking

- Think rationally
- Act like humans
- Act rationally.

According to Shapiro and Eckroth (1987), the first AI programs were developed during the 1950s. These programs could perform tasks such as playing chess. None of the programs developed in the 1960s were able to solve complex problems, although they did further the understanding of the intelligent problem-solving process. Gaming programs became popular for testing AI as this was the easiest way to compare two programs and investigate whether simple rules would be able to overcome limited memory problems. It became evident, however, that this was not the case due to the large number of move sequences to be considered.

During the 1970s, AI systems were used mainly in laboratories and incorporated specific knowledge based on the area they were assigned to. Commercial systems that were cost-effective became available during the 1980s for both government and industry purposes (Shapiro and Eckroth, 1987). With increasing use of these new systems, a lot of errors became apparent. However, in spite of these flaws, the systems continued to be used by both companies and the government. The 1990s and 2000s saw a variety of major developments in AI technology.

Applications of artificial intelligence in various fields

AI technology is applied in numerous fields, including planning and scheduling, gaming, vehicle control, medicine, robotics, language understanding and problem-solving, and speech recognition. This section will provide examples of some of these areas.

In regard to planning and scheduling, the system consists of a search engine, which uses a planned database and knowledge base to construct a plan. An example of such a system was used by the National Aeronautics and Space Administration (NASA) on board its Deep Space One spacecraft in 1999 (Jonsson *et al.*, 2000). The system was used to detect, diagnose, and recover from any problems occurring on the spacecraft. Plans were generated by the system considering limitations in time, resources, and flight safety rules. Spyropoulos (2000) discusses the application of AI planning and scheduling for therapy planning and hospital management.

As mentioned previously, one of the most popular applications of AI technology is in the area of gaming. Russell and Norvig (2003) discuss Deep Blue, a chess-playing computer built by IBM that in 1997 defeated Garry Kasparov, the then world chess champion. Another game, WarCraft, was the first game to employ pathfinding algorithms at such a grand scale, for hundreds of units in the game engaged in massive battles (Grzyb, 2005). SimCity is another example where AI has been successfully used.

AI can be used to control a vehicle without much human intervention. The Robotics Institute at Carnegie Mellon University (USA) designed the Autonomous Land Vehicle in a Neural Network (ALVINN) with the task of following roads. Successful trials with the test vehicle have indicated that the network can effectively follow real roads under certain field conditions (Pomerleau, 1989).

In the field of medicine, AI has the potential to exploit meaningful relationships within a data-set for use in the diagnosis, treatment, and predicting outcomes in many clinical scenarios (Ramesh *et al.*, 2004). 'Pathfinder' is an example of an expert system that helps surgical pathologists in diagnosing lymph-node diseases. It is one of a growing number of normative expert systems that use probability and decision theory to acquire, represent, manipulate, and explain uncertainty in medical knowledge (Heckerman *et al.*, 1992).

AI technology can expand the capabilities of robots. HipNav is an example which uses AI to create a three-dimensional model of a patient's internal anatomy. Robotic controls are then used to guide the insertion of the patient's new hip replacement (Russell and Norvig, 2003).

In the field of linguistics and problem solving, Littman *et al.* (1999) discuss PROVERB, a computer program that uses filters, an archive, and other information sources to solve crossword puzzles. A solver chooses the best candidate from solutions generated by 30 different modules. These modules can be split into five categories – word list modules, crossword database-specific modules, information retrieval modules, database modules, and syntactic modules. Word list modules ignore the clue and run every word from a dictionary that has the correct length. Crossword database modules search for similar clues from a database of previous crosswords. Information retrieval modules search online full-text sources such as encyclopaedias. Domain modules search specific domains for solutions based on specific parameters such as authors, songwriters, or actors. Syntactic modules are used to solve specific clues where it is required to fill in a blank.

According to Sharples (1996), many tasks could be made easier by controlling through speech rather than typing. Modern systems can recognize speech with little or no training compared to older interfaces, which were limited in regard to input. Stolcke (1997) lists a variety of technological areas in which speech recognition is available such as dictation software, medical equipment, and stock trading over the telephone. Speech recognition technology development is measured by the ratio of incorrectly recognized words to the number of words spoken, known as the word error rate. While the word error rate can be affected by a number of factors such as the size of the vocabulary, the speaking style of the user, whether the query is open or task-oriented, whether the system is trained for more than one user, the channel quality of the system, and background noise, the rate is not affected by the language chosen.

Applications of artificial intelligence in mining

For many years, AI tools have been in use in various mining-related applications. Bandopadhyay and Venkatasubramanian (1986) developed a fault diagnostic expert system for the longwall shearer. Altman *et al.* (1988) developed an expert system, Mine Ventilation Manager, to control the operation of a mine ventilation network system. Schofield (1992) developed MINDER, a decision support system capable of assisting the mine planner in the complex task of selecting the optimum surface mining equipment. One of the major objectives of this program was to enable integration with other mining software packages.

Denby and Kizil (1991) describe the development of an advanced computer system for the assessment of geotechnical risk in surface coal mines. The authors review the ESDS, an expert system for slope stability assessment. The paper concludes by presenting an example that illustrates how ESDS may be utilized as a decision support system at the design stage of a UK surface coal mine. Faure *et al.* (1991) developed an expert system, XPENT, for slope stability analysis.

There are numerous examples of work done in the area of mapping minerals. Kruse *et al.* (1993) used a knowledge-based expert system to automatically produce image maps showing the principal surface mineralogy developed from Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) data. Moore and Sattar (1993) developed a knowledge-based system to assist in the modelling and economic assessment of potential mineral deposits in Queensland, Australia. The system was able to be readily tailored to address specific mineral commodities and environments.

Bearman and Milne (1992) reviewed the opportunities for expert systems in the minerals industry, and explored potential future developments and applications for the industry. Romans (1993) provides examples of application of knowledge-based systems in the minerals industry leading to substantial savings. Kizil *et al.* (1995) also summarized the use of AI applications in mining. They mentioned Waller and Rowsell's (1993) work on the development of a system named '*Intelligent Drilling Control*' using AI in petroleum industry. The system aimed to optimize the drilling process, and measure the real-time pick consumption and calculate the drilling costs.

Deliormanli *et al.* (1995) developed an expert system software named EMQDS (*Expert Marble Quarry Design System*) to select appropriate equipment, assess the work-force, and conduct a financial analysis for marble production.

Toll (1996) discusses the application of AI systems for geotechnical applications. According to the author, a significant number of systems have been developed for site characterization, classification of soils and rocks, foundations, earth retaining structures, slopes, tunnels and underground openings, mining, liquefaction, ground improvement, geotextiles, groundwater/dams, roads, and earthworks.

Morin (2001) discusses the integration of support elements such as expert systems, numerical models, data analysis and visualization tools, and simulation to bring added functionality and intelligence to the mine design and planning system. According to the author, the integration of these elements, if feasible, would form an intelligent design system with decision-support capabilities that exceed anything currently available on the market.

'*Expert and knowledge based systems, probably the most popular AI tools, have found their way into a number of computer-based applications supporting everyday mining operations as well as production of mining equipment*' (Kapageridis, 2002). This study mentions the use of AI tools for exploration and reserve estimation, geophysics, rock engineering, mineral processing, remote sensing, process control and optimization, and equipment selection. Foloronso *et al.* (2012) developed an expert-based mineral identification system to teach undergraduate students. They were able to promote effective and meaningful learning of scientific observation in the area of Earth Science. According to Knobloch *et al.* (2013), mineral predictive maps can be created with the help of artificial neural networks (ANNs) which use a comprehensive data-driven modelling approach. Based on a '*self-learning' process, this AI technology can be used to interpret almost any geoscientific data for generation of both qualitative (prediction of locations) and quantitative (prediction of locations, grades, tonnages) mineral predictive maps. By analysing the footprints of known mineralization in the framework of available geoscientific data, the approach generates trained ANNs that are further used to generate predictive maps*.

Fuzzy logic

Traditional science is centred on the binary status view that a statement is either entirely true, or entirely false. However, according to Kosko (1999), '*fuzz*' includes statements that are only partially true in order to define vague terms that have entered human language. This way of thinking has generally not been accepted by modern science. A set is a binary structure to which objects belong. An object either belongs to a set or it does not; sets do not allow for partial membership. Depending on whether or not they belong to a set, objects are represented by a 1 or 0. However, a fuzzy set allows for partial membership. Fuzzy logic systems use fuzzy sets to convert inputs into the correct outputs. Like a human expert, a fuzzy logic system uses rules of thumb to determine what action must be taken in a certain situation. These are called *Fuzzy If-Then* rules and they follow the form *if x is A then y* is *B* where A and B are linguistic values defined by the fuzzy sets on the universe of disclosure X and Y (Castillo and Melin, 2008). In the above rule, *x* is *A* is defined as the antecedent or premise while *y* is B is called the consequent or conclusion. An example of such a rule in our everyday life can be *if service is great then tip is greater than 15%*. The curse of dimensionality says that there will always be a limit to the number of rules that can be used due to the memory limits of computer chips. A membership function maps the object values within a set and can take a number of forms. Bezdek (1996) lists the following five basic operations that are used to manipulate fuzzy sets:

- ➤ Equality
- ➤ Containment
- ➤ Complement
- ➤ Intersection
- ➤ Union.

Fuzzy logic began in Ancient Greece with the philosopher Zeno. According to Kosko (1999), Zeno posed the question: *if we remove the grains from a pile of sand one at a time, at what point does it cease to be a pile*? The fuzzy answer is that the pile leaves the set of piles of sand as smoothly as the individual grains are taken away from it. At the turn of the 20th century, Bertrand Russell stated that '*everything is vague to a degree you do not realise it until you try to make it precise*'. Russell said that during the transition phase, objects would spend the majority of their time in a mix of the two states. In the 1920s Jan Lukasiwicz looked at these theories as an extension of binary logic. He stated that all statements are either true or false to some degree, but that the 'true' and 'false' scores must add up to 100%. In 1937, Max Black drew the first graph of a fuzzy set. However, the philosophical community largely ignored these views due to their attitude towards logic at the time. The term '*Fuzzy*' was introduced by a paper by Lofti Zadeh, the chairman of the electrical engineering department at the University of California, in 1965. However, it was decades before his work received recognition in the form of a medal of honour from the Institute of Electrical Engineers in 1995.

According to Kosko (1999), one of the first devices to use fuzzy logic was a kiln for F.L. Schmidt and Co. in Copenhagen, in 1980. The coal feed rate was reduced if both temperature and oxygen levels were high within the kiln. One of the most notable developments in the use of this technology was the Sendai subway railway system developed by Hitachi in 1988. The system replaced train drivers along the 13.6 km long, 16-station track. The introduction of the system has led to a smoother ride for passengers, with a 10% reduction in energy consumption compared to human drivers (Kisko, 2005).

Many of the earliest applications of fuzzy logic were designed to be used by organizations. The first home appliance to use fuzzy logic was a washing machine developed in 1990 (Wakami *et al.*, 1996). The optimum washing time was determined through outputs from a washing sensor and fuzzy logic technology. The washing sensor used a light-emitting diode and a phototransistor to measure the transmittance of the water. The rate at which the light transmittance decreased indicated whether the dirt in the machine is muddy or oily, which in turn indicated whether there was a light or heavy amount of dirt in the washing machine. Fuzzy logic used these inputs to determine the optimal washing time.

Fuzzy logic technology has also been used to stabilize videos shot with amateur video cameras. As video cameras became smaller and lighter, the effect of hand jitters became more noticeable. The image stabilizing system consists of a motion detection chip, interpolation processing chip, field memory, and microprocessor to hold the fuzzy interference. The image is sent to the field memory while also being processed by the motion detection chip. The motion detection chip looks for correlation between images to detect the amount and direction of movement. The field memory then repositions the image and uses the electronic zoom function of the camera to enlarge the compensated image. Fuzzy logic is used to distinguish between a shaking video and a moving subject. This is determined by whether all objects within the image are moving in the same direction or if they are moving in different directions.

Fuzzy logic technology, when combined with an infrared ray detector, can be used to assist an air conditioner in efficiently cooling the occupants of a room through knowledge of the current temperature and the number of occupants and their positions. The rotating infrared ray detector creates a two-dimensional thermal image with each element given a temperature value. The fuzzy logic algorithm then performs three tasks – removing the background, identifying each occupant, and expanding the region of each occupant. In order to isolate the occupants from the background, the algorithm identifies areas where the average temperature for that group of elements is higher than a set value. Given that a peak temperature would represent each occupant, the algorithm identifies elements whose temperature is higher than the eight elements surrounding it and assigns each of these peaks a number to identify the number of occupants. The algorithm then expands the area covered by each occupant by lowering the threshold temperature in order to expand the area covered without increasing the number of peaks.

Fairhurst and Lin (1985) discuss the application of fuzzy methodology in tunnel support design. According to the authors, '*a decision system for tunnel support design allows questions to be posed and answered in relation to the information stored in a rafael design knowledge base*.' Such systems will be successful depending on their ability to extract information from geology, rock mechanics, and tunnel technology and translate it into a form or forms that help the user to make a more intelligent decision for tunnel design. The study presents a preliminary discussion of approaches to the development of such systems.

Fuzzy logic technology can be used to compensate for friction in machinery. Friction is based on both the position and the velocity of an object and is difficult to predict with an accurate model (Liu *et al.*, 2006). However, due to the large impact of friction at low velocities, developing such a model is important. Experts designed a fuzzy logic control to approximate such phenomena. A fuzzy logic system has also been used to identify suitable advisors for call centre customers. According to Shah *et al.* (2006), companies are aware that a happy customer can lead to repeated business. It is therefore important to match the correct advisor to each customer. There are five behaviour dimensions of the advisor that can influence customer satisfaction; these include mutual understanding, authenticity, extra attention, competence, and meeting minimum standards. Different customers would react in different ways to each of these, so it is important to know which will work best for each demographic of customer. Fuzzy logic can be used to infer the goals of the users. To develop such a system, the company must collect data, cluster and analyse the data, identify the separate categories, categorize both consumers and advisors, identify the critical factors and derive their membership functions, develop if-then rules, implement the fuzzy interference process, test the system in a real-world environment, and validate the system from feedback received.

Beynon (2008) discusses the use of fuzzy logic in decision trees. Decision trees allow for greater interpretation of an analysis by humans. The root node of each tree is split into leaf nodes to further classify objects. Each leaf node is created using fuzzy if-then rules. Decision trees increase the understanding of complicated situations and can be applied to a variety of scenarios. Beynon (2008) applies a fuzzy decision tree to the complex situation of company audit fee evaluation.

Conclusions

The School of Mining Engineering at UNSW Australia employs a VR simulator that is used to replicate mining situations in a comfortable, safe, and forgiving environment. The VR system offers many benefits to its users, including flexibility in time and place, and the rate and privacy of the learning experience. The system has a variety of uses, including the development of understanding and the retention of learning, customized on-the-job training, fault finding, easy communication of complex data, evaluation of the consequences of poor decision-making, trainee assessment, identification of flaws in training programmes, and accident identification and reconstruction.

The modules developed at the School can immensely benefit from the use of both AI and fuzzy logic technologies. In order to improve the interactive feature of the system, the user must be able to control the system in a more natural way. Currently, all the modules are operated in the AVIE through an iPad environment. However, speech and gesture are the most natural way in which humans interact with others. According to iCinema (2012), a motion capture function that can recognize the gestures of up to five people at once is currently offered by the AVIE system. However, the current mining simulations do not utilize this feature. Integrating this feature will definitely improve the interaction in the AVIE facility and will add more realism required specifically for training effectiveness in this environment. To reduce the word error rate for this new function, the control could be initially limited to a number of key phrases.

Using a similar technology as in air conditioners, infrared detectors can track the movement of people in this environment and then through the use of AI make changes to the way the module operates. As an example, different actions by a group of trainees can lead to different outcomes. Another application of this technology is in the ViMINE module. This module involves decision-making based on input from the user.

An overview of the historical and current uses of AI and fuzzy logic technologies, as well as how each form of computing works, has been conducted, and some applications of both AI and fuzzy logic provided. From this study, it can be seen that there is a lot of opportunity for applying AI and fuzzy logic technologies to the current VR technology used at the School in order to benefit learning and teaching. Further detailed studies will look into the specifics of how these technologies could be integrated into the current system. A pilot study will initially be conducted on one of the modules to test the feasibility of this integrated technology.

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