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A Small-scale Implementation of Industry 4.0

Faisal Aqlan, Mohammed Alabsi, and Ethan Baxter
Penn State University, The Behrend College
Erie, PA 16509

Sreekanth Ramakrishnan
IBM Corporation
San Jose, CA 95141

Abstract

This paper discusses the implementation of Industry 4.0 in an educational setting. Simulation, virtual reality, analytics, robotics and automation, and 3D printing are integrated to develop a small-scale production line for producing and inspecting 3D printed parts. The system consists of a robot and controller, programmable logic controller, 3D printer, machine vision system, conveyor belt, 3-phase motor and motor controller, webcam, PC and monitor, Raspberry Pi computer, pneumatic system, beam sensor, simulation software, and VR equipment. The system components are connected via ethernet cables running to a basic ethernet switch. An ethernet router is also connected to the switch to resolve IP connection attempts by the connected components. A mini CNC machine is used to drill holes on small metal parts that are assembled with 3D printed parts and plastic bricks to make a car toy. A robot is pre-programmed to perform the assembly of the car toy and a Cognex® camera is used to inspect the parts. Deep learning models are used to predict the remaining useful life of the drilling bits.

Keywords
Industry 4.0, Automation, Virtual Reality, 3D printing, Simulation

1. Introduction
In the past few decades, the fourth industrial revolution (aka Industry 4.0) has emerged as the latest advancement in the manufacturing paradigms. The building blocks of Industry 4.0 include autonomous robots, simulation, horizontal and vertical integration, industrial internet of things, cyber security, additive manufacturing, virtual and augmented reality, and big data analytics. These building blocks are shown in Figure 1.The first industrial revolution, which began in the 1700s, was the use of water and steam power and the creation of factories. The second revolution, which began in the early 20th century, saw the addition of electrical power and mass production that allowed factories to be placed anywhere in the world. The third revolution added automation and the use of robots to manufacturing in the 1970s. Figure 2 shows the evolution of manufacturing technology. Industry 4.0 is only possible because of a few advances in technology including: (1) reduction of computing cost, (2) rise of open communication standards which has allowed, and sometimes forced, manufacturers to create devices that can communicate with each other, (3) miniaturization and integration of computing devices onto a single die. This has allowed manufacturers to integrate computing, memory, and communication onto a single

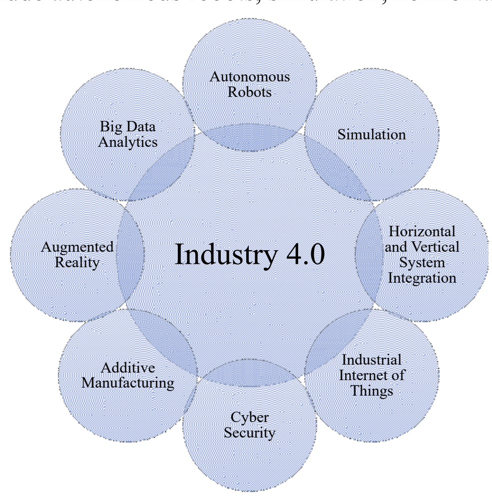


Figure 1: Building blocks of Industry 4.0

chip, and (4) rise of the internet. The internet has created a pipeline that allows information to travel quickly and cheaply between buildings, factory locations and even different manufacturers at different levels in the supply chain. Industry 4.0 has grown out of several needs. The first and most obvious is the need to reduce the cost of production. As China and other emerging economies have increased the percentages of world manufacturing, other countries especially in Europe and the US have seen a much larger need to reduce manufacturing costs. Industry 4.0 offers the promise of reducing manufacturing costs and increasing the precision and quality of manufactured products. Industry 4.0 also offers the chance for increased worker safety in environments and materials that could be hazardous. It allows for lower initial capital costs and faster, more flexible manufacturing. Assembly lines and mechanical automation were built with the expectation that a product lifecycle would be measured in decades. Current product lifecycles are measured in months. Manufacturing systems that are flexible and quickly reconfigured through software allow manufacturers to limit sunken costs in systems that can only be used for one product.

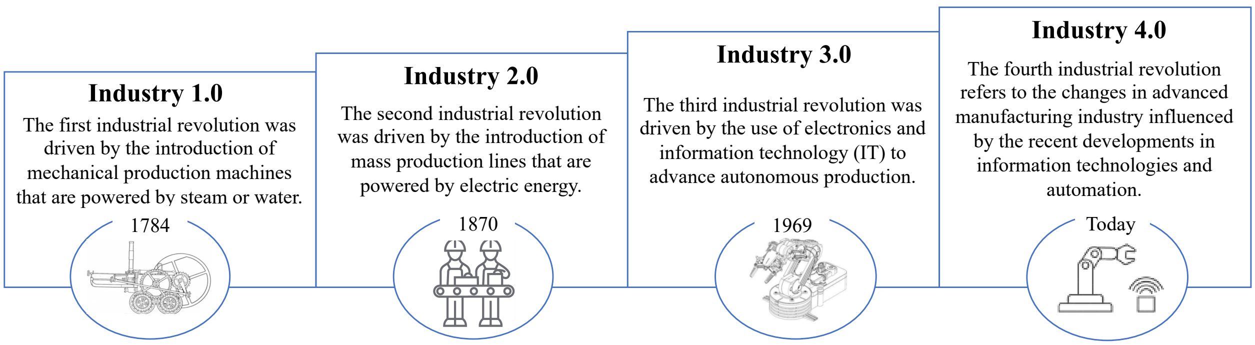


Figure 2: Evolution of manufacturing technology

2. Relevant Literature

Many researchers and practitioners are giving significant attention to Industry 4.0 due to the significant changes it causes in industrial sectors and its numerous benefits to manufacturing organizations. According to Pacchini et l. [1], Industry 4.0 is "a set of disruptive digital and physical technologies that offer new values and services to customers and organizations." A model was proposed to measure the readiness of manufacturing organizations for the implementation of Industry 4.0. The model comprises the eight technology enablers that are the most relevant based on existing literatures and it was tested in automotive industry. The challenges for implementing Industry 4.0 in manufacturing industries has been discussed [2]. The study found that the most pressing challenge is the lack of technological infrastructure. A conceptual model, in the form of causal loop diagram, was presented [3]. The model considers the variables that support the implementation of Industry 4.0 to energy industry in developing countries. A study proposed a framework to identify the critical success factors and challenges for industrial augmented reality implementation projects [4]. It was revealed that organizational issues are more relevant for the implementation of augmented reality to support Industry 4.0 in manufacturing industry. A framework for implementing risk management in Industry 4.0 was proposed [5]. The analysis showed that the majority of common risk factors in the manufacturing area are related to information security and the risks may occur more frequently in Industry 4.0. A study argued that in addition to considering the technical aspects of industry 4.0, it is necessary to understand the socio-technical requirements to ensure successful implementation. Table 1 summarizes the studies on Industry 4.0 implementation.

Table: Summary of relevant literature on Industry 4.0 implementation

Study	Focus of the Research	Application Industry
[1]	Readiness of manufacturing industries for implementing Industry 4.0	Automotive industry
[2]	Challenges facing manufacturing industries to implement Industry 4.0	Leather industry
[3]	Impact of Industry 4.0 implementation to sustainable energy transition	Energy industry
[4]	Challenges and success factors for augmented reality in Industry 4.0	General manufacturing
[5]	Aspects of risk management implementation for Industry 4.0	General industry
[6]	Socio-technical considerations in Industry 4.0 implementation	General industry
[7]	Challenges of implementing Industry 4.0 in discrete manufacturing	Discrete manufacturing
[8]	Challenges for implementing Industry 4.0 construction industry	Construction industry
[9]	Learning factory for industry 4.0 education and applied research	Educational setting
[10]	Using interdisciplinary demonstration for teaching Industry 4.0	Educational setting
This study	A small-scale implementation of Industry 4.0 for car toy assembly	Educational setting

In discrete manufacturing, some problems that can occur during the Industry 4.0 implementation [7]. The study presented strategies to avoid these problems such as running random simulations followed by result verification. In construction industry, a study showed that critical factor affecting the successful implementation is social and technical factors [8]. Other studies discussed the utilization of learning factory and interdisciplinary demonstration for teaching Industry 4.0 concepts and conducting applied research [9-10]. This paper presents the implementation of Industry 4.0 in an educational setting to teach the concepts of Industry 4.0 and provide students with practical hands-on experience.

3. Methodology

The integration of the building blocks of Industry 4.0 in order to develop a small-scale implantation in an academic setting is proposed. The implementation is performed in three phases: system design and implementation, industry 4.0 application, and ANSI/ASI 95 integration [11]. The system is developed in three phases (see Figure 3). In phase 1, system requirements were identified and the equipment was acquired, installed, and tested. Phase 2 involves developing Industry 4.0 applications to teach students the concepts of simulation, virtual reality, 3D printing, machine vision, and analytics. Phase 3 which involves the integration of ANSI/ISA 95 model is in progress.

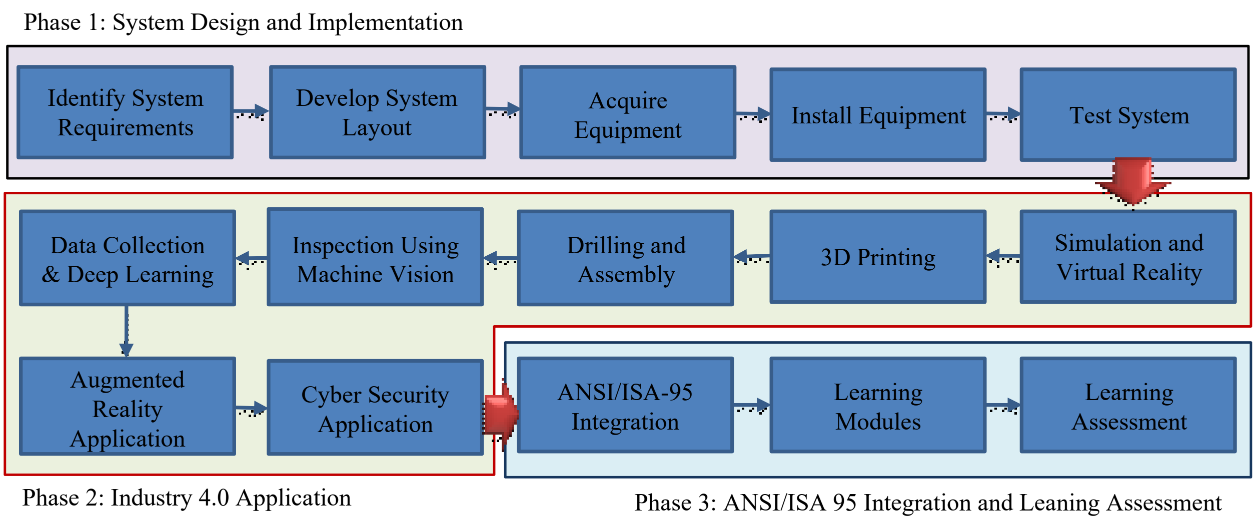
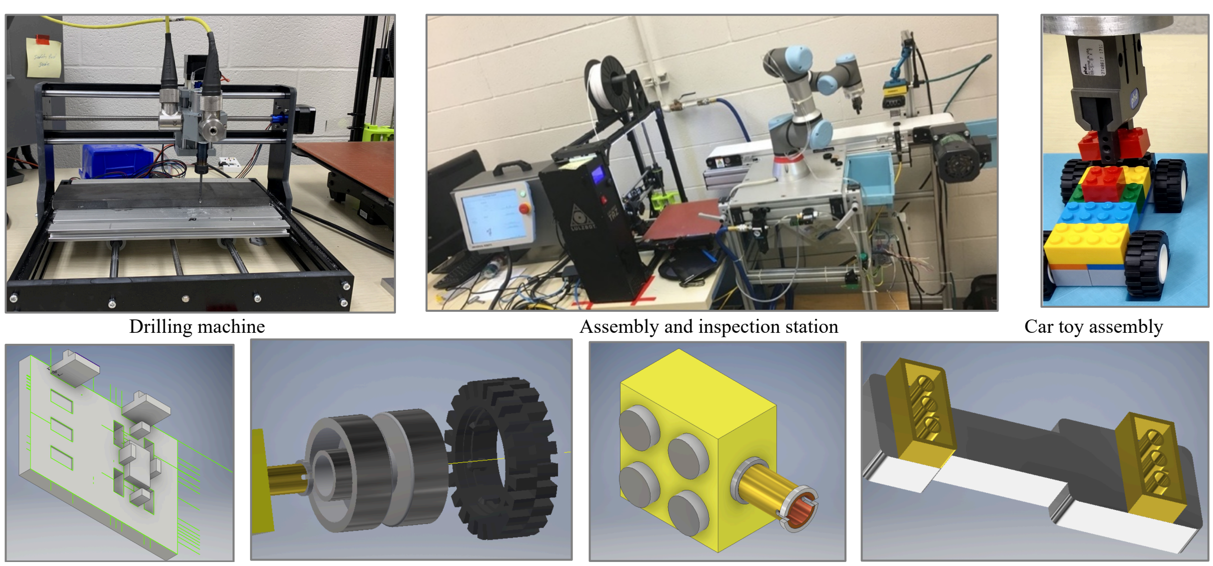


Figure 3: Industry 4.0 implementation

The system is designed to produce and inspect car toys. Sample pictures are included in Figure 4. The car toys consist of plastic bricks assembled with 3D printed parts and machined metal parts made in the lab. A UR 3 robot was pre-programmed to perform the assembly of the car toy.



Sample CAD models for a fixture and car toy parts

Figure 4: Sample picture of the Industry 4.0 system implementation

An example of the steps in the sequence program to test the 3D printed parts are as follows: 0. PLC waits for printer to finish printing, 1. PLC tells the robot to run the part-pickup sequence and then waits for robot to return a "done" signal, 2. PLC runs conveyor belt forward until the motion sensor is triggered, 3. PLC triggers the camera and waits for it to return a partgood or partbad signal, going to step 4 or 5 depending, respectively, 4. PLC runs belt until motion sensor is unobstructed again and returns to 0, 5. PLC reverses belt for a second and then triggers the robot remove sequence, waiting for the done signal before returning to step 0.

Simulation and virtual reality were implemented in RoboDK software [12]. First, a CAD model was developed for the system and imported to the software. Second, a program was developed in RoboDK for the car toy assembly. The program was tested in RoboDK and then imported to the physical robot. Virtual reality is also available in RoboDK and we used HTC Vive headsets to visualize the simulation while doing the offline programming. Figures 5 and 6 show the system model RoboDK and the automated assembly department of our virtual factory, respectively.

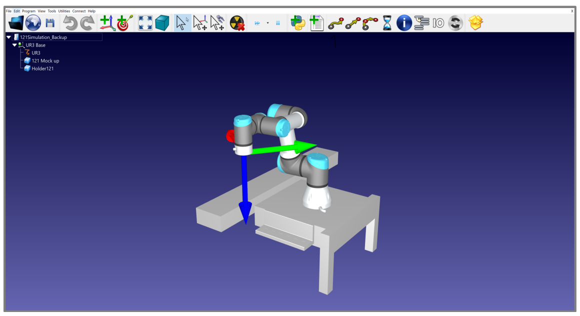


Figure 5: CAD model of the system in RoboDK

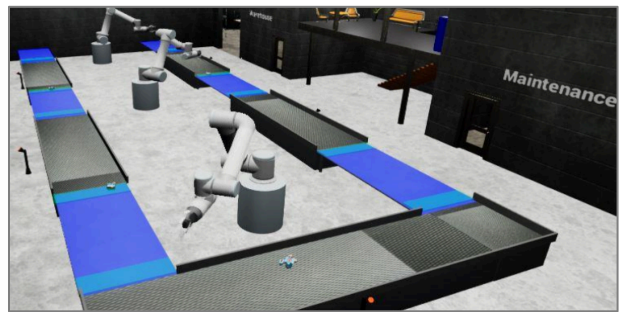


Figure 6: A snapshot of the virtual factory

3.1 Proposed Remaining Useful Life Estimation Scheme

Figure 7 shows the proposed scheme for the drilling bit Remaining Useful Life (RUL) prediction. The process starts by data collection from accelerated failure testing followed by feature extraction from vibrations data and at the end training and testing the Deep Neural Network for RUL estimation based on extracted features.

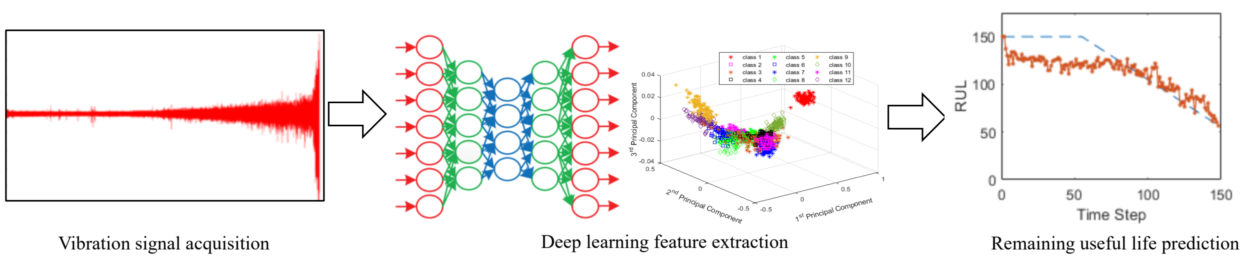


Figure 7: RUL prediction scheme

For vibration data acquisition, the drilling experiment was conducted using Genmitsu CNC machine to drill holes in 1/5 in. carbon steel bar (see Figure 8). Two single axis accelerometers were mounted perpendicularly to measure radial vibration on x and y axes (see Figure 9). The accelerometer outputs 100mV/g signal which is sent to the signal conditioner CMCP590. The signal conditioner outputs 4-20 mA signal and the out is connected National Instruments Data Acquisition card DI-1100. It is worth mentioning that NI DI-1100 accepts analogue voltage input, hence a 200 Ω resistor is installed in parallel to the 4-20 mA signal input. In this case, current analogue input signal is converted into voltage analogue signal ranging from 0.8-4 volts. The spindle motor was powered using an external power supply and the rotational speed was fixed at 9000 rpm throughout testing. Drilling process was carried out without any external coolant in order to expedite the bit wear and the accelerometer data (sampled at 1000 Hz) was used to measure vibration throughout testing. 3 bits were used and each bit was able to drill 5 holes before complete wear.

Deep Learning is becoming more popular for prognosis and health monitoring applications. Traditional artificial neural networks suffer from limited capacity to learn nonlinear and more complex patterns due to their shallow structure [13]. Deep Neural Networks (DNNs), thanks to their deep structure, perform better for applications that involves nonlinear relations and requires extensive mining. In this paper, Long Short-Term Memory (LSTM) DNN is used to predict the RUL of a drilling bit based on extracted features from the data. LSTM, a variation from Recursive Neural Network, was developed to learn long term dependencies. LSTM networks are not well suited for feature extraction applications and Convolutional Neural Networks (CNNs) are combined with LSTM to boost feature

extraction capability [2]. However, given the simplicity of the application and limited components that are subject to wear it was decided to utilize only LSTM network. Given the limited feature extraction capability of LSTM network, Fast Fourier Transform (FFT) coefficients were fed into the network instead of the time domain data. FFT coefficients carry important spectral features which improves feature extraction capability and RUL estimation consequently.
The finished parts of the car toy are inspected using Cognex® camera and In-Sight vision system. Figure 10 shows a snapshot of the machine vision software that is used to inspect the finished parts.

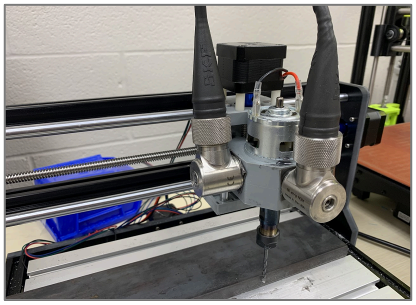


Figure 8: Attaching accelerometers to the CNC machine

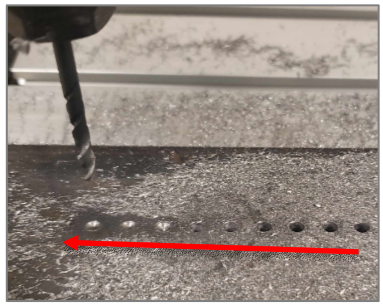


Figure 9: Drilling bit deterioration after drilling multiple holes

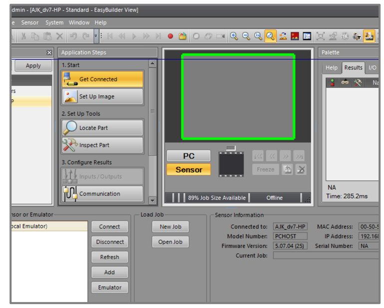


Figure 10: A snapshot of the machine vision software

4. Results and Analysis

Three drilling bits were considered for the experiment: two of them were used for training the DNN and one for testing. Figure 11 shows the prediction results using the training data. It was assumed that wear mechanism is linearly dependent on drilling time which is represented by the blue dotted lines while the model prediction is represented by the brown curve. The data was preprocessed such that idle time between holes was truncated and the data was normalized to have zero means. Degradation trend was successfully captured considering both cases and the root mean squared errors were: 38.122 and 20.55.
The model was tested to predict the RUL of a drilling bit that was not considered during model training. Figure 12 shows the actual degradation trend compared with the model output. The overall degradation trend was captured successfully and the root mean squared error is 18.94. The reduced RMSE for testing case compared with training was mainly caused by the relatively short testing data set. It is clearly shown that deep learning analytics provided excellent outlook about the drilling bit life expectancy which is a building block for industry 4.0.

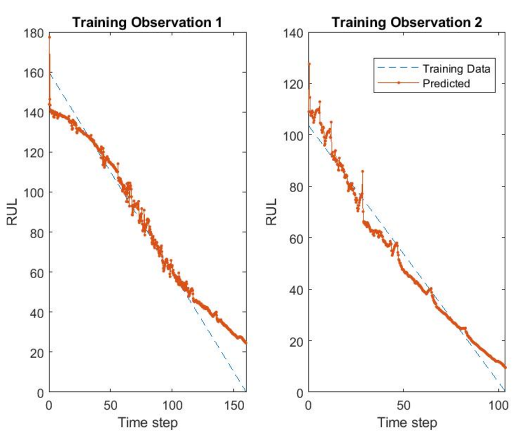


Figure 11: RUL prediction using training data

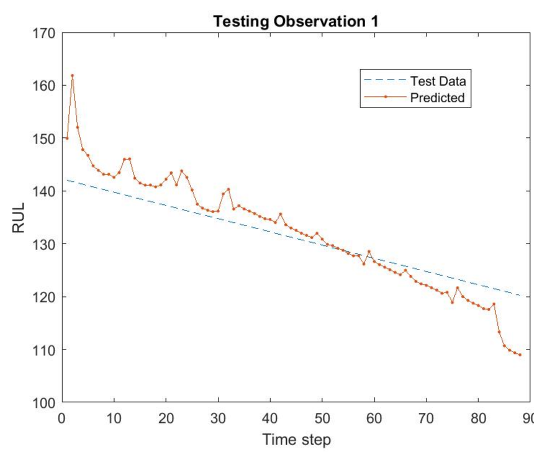


Figure 12: RUL prediction using testing data

5. Industry Perspective: IBM Model Factory

The small-scale Industry 4.0 system presented in this study was also aligned with the IBM Model Factory, see Figure 14 (www.ibm.com). According to IBM, Industry 4.0 is not only about connecting machines to the cloud; it is also about focusing on connecting the "factory activities." The system proposed in this study will be integrated with IBM Cloud and Watson IoT™ in order to collect and process IoT data quickly and easily. Figure 14 shows the proposed system integration.

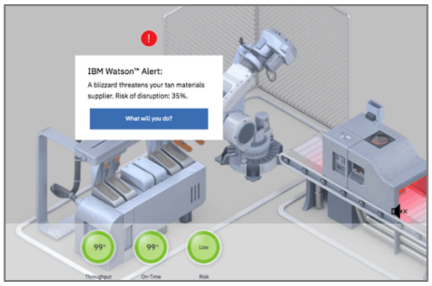


Figure 13: A snapshot of IBM Model Factory

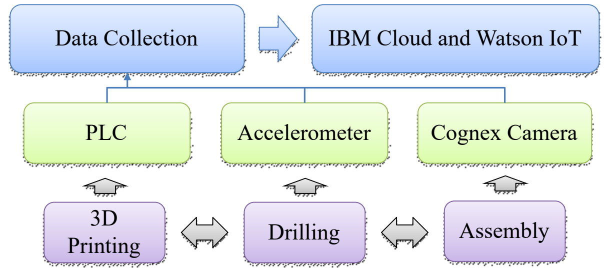


Figure 14: Integration with IBM Cloud and Watson IoT™

6. Conclusions and Future Work

This paper presented a small-scale implementation for Industry 4.0 in an educational setting to teach students the concepts of Industry 4.0. The system was used to train undergraduate students and high school and community college instructors on Industry 4.0 concepts and applications. This educational system will prepare students for the next industrial revolution and provide them with practical hand-on experience. Future work will focus on the development of augmented reality and cyber security applications as well as integration of ANSI/ASI 95 framework and Watson IoT™.

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