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A Cyber-Physical System (CPS) for Automating Additive Manufacturing Process with Industry 4.0

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ABSTRACT
This paper focuses on the development of a cloud-based cyber-physical system (CPS), where various types of optimization models, approaches, and monitoring systems will be carried out. The CPS, an enabler for Industry 4.0, automated the manufacturing process by bringing all the optimization processes and various steps into a cloud framework. This CPS created an autonomous network where all the details went directly to the web platform. Thus, appropriate process parameters, based on the performance value evaluation form the previously generated algorithm, will go directly to the additive manufacturing machine (3D printer). Microsoft Azure was used as cloud platform. Raspberry pi will be used to connect the 3D printer to the Azure IoT hub and access the Azure machine learning studio, where the generated algorithm will automatically evaluate and determines the most suitable value. In this study, Fused Deposition Modeling (FDM), one of the most used methods of 3D printing was used. The property (tensile strength) of a 3D printed gear was considered as the output parameter for optimization. The methodology of the CPS starts with receiving customer demand (input data) directly at Azure IoT hub. Then the system will transmit suitable output data automatically through the raspberry pi module to the 3D printer. Subsequently, the printing process will be completed as per the instruction from the system. The benefit of this project lies in the successful implementation of an automated system, thereby minimizing human monitoring for additive manufacturing process via cloud platform in Industry 4.0 perspective.

Keywords: 3D printer, IoT, CPS, Autonomous, Microsoft Azure

1. Introduction
As a part of the fourth industrial revolution, the manufacturing industry is moving significantly fast towards complete automation [1]. Additive manufacturing is an element of the Industrial Revolution 4.0 where a product is fabricated layer by layer directly from a computer-aided design (CAD) [2]. It can generate a complex geometry part in a short amount of time with low wastage [3]. There are many researchers currently working with additive manufacturing to develop a new way to fabricate part layer by layer and also improve the existing process. Fused deposition modeling is largely used to build prototypes and different customized parts [4]. That is why there are many research papers about the parameter optimization of fused deposition modeling. In FDM, where complex shape products are manufactured; Customer, Manufacturer communication needs to be very good to manufacture the desirable object. The goal of this paper is to make this communication easy using the elements of Industry 4.0 like CPS and machine learning to get the desired product with minimum waste, less human monitoring, and less human interaction. To build a sound connection between two parties, a cloud-based platform can be used. This cloud-based platform can make business easier by making communication between buyers and manufacturers a lot faster and effortless. To get the optimum parameter for specific part, Artificial Neural Network (ANN) is used. This paper is focused on the tensile strength properties of a 3D printed part. A standard spur gear is fabricated with Fused Deposition Modelling using a FDM machine (Fig.1).

2. Literature review
From the conventional manufacturing machines like Lathe machine, Milling machine, Drilling machine manufacturing industry moved to Computer numerical controlled machine which is faster, easier, and more efficient. Now as the world is moving forward with the 4^{th} industrial revolution, the use of additive manufacturing where a product is printed layer by layer is increasing rapidly [5]. Additive manufacturing has existed for over thirty-three years. But this technology is recently getting recognition because of its ability to fabricate complex shape parts with low or minimal waste. The process builds objects by adding material in a layer by layer fashion to create a three-dimensional (3D) part [6]. It is used to manufacture particularly complex structures not attainable by other manufacturing methods [7]. There are different kinds of

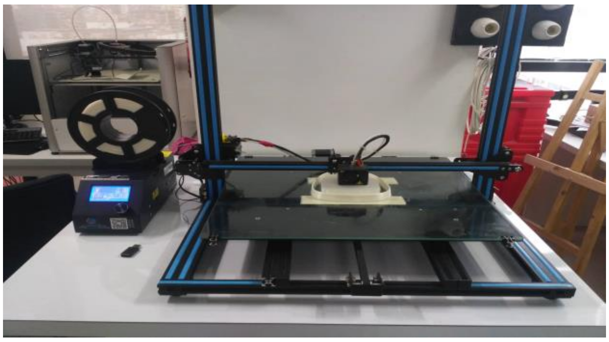

Fig.1 CREALITY CR-10 machine (EMK center)

additive manufacturing including filament extrusion (like fused deposition modeling), photopolymer curing (like stereolithography), powder sintering (like selective

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laser sintering), and sheet lamination (like laminated object manufacturing) [8]. Additive manufacturing is now used in the Aerospace industry to build different complex shape components or build a prototype. It is also used in automotive, Machine tool production, architectural prototype, and also in the food industry [9]. Fused Deposition Modelling is widely used because it can produce high-quality complex geometry shape parts with a different kind of thermoplastic polymer [10]. Different thermoplastic like Acrylonitrile butadiene styrene (ABS) [11], Polylactic acid (PLA) [12] is used in FDM. There are many different methods to select the polymer for an experiment [13]**.** Many parameter optimization tools including Taguchi [14], ANN [15], Genetic Algorithm [16] are used to optimize the parameters. Manufacturing industry is moving forward with each revolution. The first industrial revolution was after the invention of the steam engine. The second and third revolution was followed by mass production and the use of electronics [17]. In the fourth revolution elements like the Internet of things, smart factories, big data are used [18]. This concept of Industry 4.0 is based on the integration of information and communication technologies. A Cyber-physical System (CPS) is used to control and monitor all that information and tasks [19]. Different fields including the automobile industry, machinery industry, iron and steel metallurgy, energy production, and also transport and logistics use this Cyber-Physical System now [20]. Currently, there is no system with parameter optimization that connects an FDM machine to control and monitor the fabrication process with a sound connection between buyer and manufacturer. In additive manufacturing, information needs to be transparent to get a customized product with an optimized parameter. In the manufacturing industry especially in additive manufacturing, CPS can be beneficial in making the whole process more advanced. This can be applied in additive manufacturing to combine the parameter optimization, remote controlling the machine, to build a sound connection between a buyer and manufacturer. To create a Cyber-Physical System, a cloud-based platform like Microsoft Azure is used where data can be stored and optimized. In Microsoft Azure, a lot of data can be stored and be easily analyzed and optimized. This can be used to analyze the input parameters for the FDM machine.

3. Design for additive manufacturing

According to research [21], this paper selects a gear (Fig:2) geometry to determine the dimensional accuracy of parts newly generated by the FDM printing machine. The sample shape of the shaft can be easily measured and analyzed. 3-dimensional parameters are required for measuring the standard component.

There are 5 sets of process parameters with orthogonal tests to enhance the accuracy and efficiency of the experiment. Finally, based on the above 5 sets of process parameters, the parts will be generated by the FDM printing machine. This article tests the normal parts one by one to get a collection of experimental samples [22]. This experiment will be performed by selecting the 3D printer, as shown in Fig. 3. PLA is the experimental material chosen. In this experiment, the extruder nozzle temperature is held at 210 degrees Celsius, the hotbed temperature is set at 50 degrees Celsius, and the ambient temperature is set at 25 degrees Celsius. The extruder nozzle material is brass, and the inner diameter is 0.4 mm. It is possible to calculate the dimensional parameters of the regular component with a micrometer. By measuring the difference between the real scale and the theoretical size, dimension errors can be obtained.

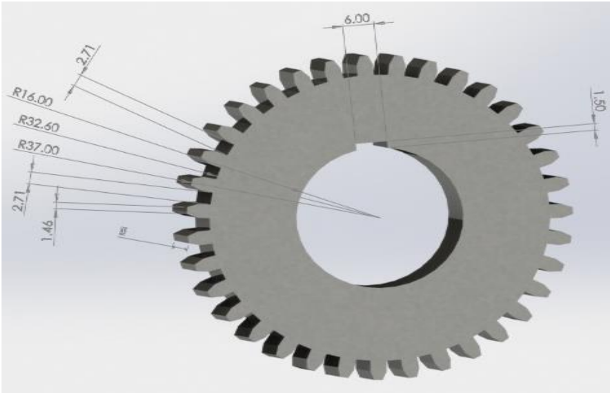


Fig.2 FDM standard spur gear

3.1 Framework for a cyber additive design for manufacturing

Cyber additive design and manufacturing are simulating the models over the cyber network for the continuous development of products and their resource upgradation [23]. Additive manufacturing can get an extra edge with the help of a cloud-based smart system that can connect with its CAD model and use cyber resources. Here CPS system is used to improve the quality control along with CAD model synchronization inputs taken from cloud and machine capability. Based on AM product details and resource ability in the cloud system, CPS can optimize the desired process parameters to improve the product as well as CAD component models. A schematic of the cyber additive design and manufacturing framework is shown in the fig.3. It consists of input component designs, knowledge base, IoT device (Raspberry Pie), smart cyber agent, and optimal AM processes for dynamic output selection. The knowledge base was generated by the compilation of AM product database, subject matter feedback, and best practices from AM original equipment manufacturers. From the digital designs and user requirements, the input component characteristics were extracted. Because of the integration of technologies, the risk of cyber threats has increased [24]. So, a secured Cloud-based system like MS Azure will be used to optimized data and send the information to slicing software. Over all it is a dynamic system that will print a product with optimized process parameters (optimized in cloud system) selection for part fabrication based on AM machine specification and resource availability in a cyber-environment.

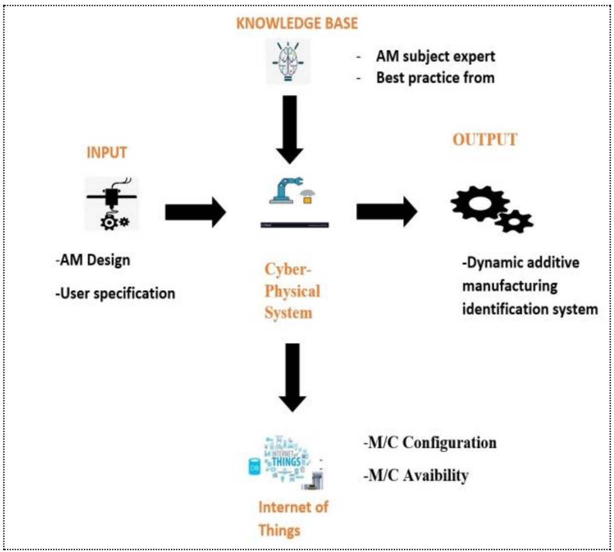


Fig.3 Data-Driven process parameter optimization and manufacturing

4. Development of Machine learning algorithm with Microsoft Azure

Microsoft Azure was chosen for the machine learning portion on this project, among several other cloud services like Amazon web service (AWS), Google cloud platform, IBM cloud, etc. There were a couple of reasons to choose this platform. One of them is user-friendliness. This platform is straightforward to operate compared to other cloud services. This platform has a unique option to run any sophisticated machine learning algorithms without writing any code.

The multiclass decision-tree approach was used here. This particular method demonstrated greater accuracy over a prolonged period than other methods. A single decision tree can't give the best prediction result for this reason prediction from a large number of trees is taken to get a highly accurate result. Trees combined are called the 'ensemble method' [27]. So, the decision forest algorithm is a classification learning technique for the ensemble.

First multiple decision trees are built and then the most common class of output is selected. Voting is a form of collection, where every tree produces a non-normalized frequency histogram of labels in a classification decision forest. These histograms are summed up by the aggregation process and the result is systemized to get the "probabilities" for each label. The trees with high reliance on prediction have a greater influence on the ensemble's closing decision. A string of simple tests are performed, for each class in each tree, which expands the tree formation levels until a leaf node (decision) is found [25]. Fig.4 is showing a portion and some nodes from one of the trees generated during the training process.

4.1 Development of a multiclass Decision Forest model

'Hyperparameter' tuning searches for a set of values in the 'hyperparameter' space that will optimize the model architecture. This is different from tuning the parameters of a model where feature space is looked for, minimizing the output [26]. Some hyperparameters were set for a multiclass decision tree by which the model was trained.

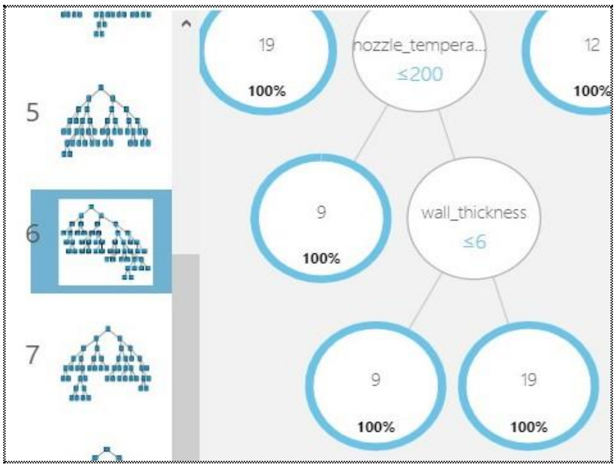


Fig.4 Portion of the structure of a trained decision tree

Every hyperparameter has its benefits and drawbacks. If we set the depth of decision trees too high, the training data will be overfitted without capturing the useful patterns which are required, which will cause a poor testing error. Setting it too low could give it little flexibility to capture patterns and create underfitting. The number of min_sample_split denoted the minimum number of nodes within an internal node. Min_sample_leaf can't be split any farther; it is the base of the tree, so for this case, we just kept it 1. It is used to avoid the overfitting of the decision tree. All the hyperparameter values that were used were shown in fig.5.

4.2 Development of a machine learning model

Once we have set all the decision tree hyperparameters, we split the data for training purposes. The split percentage used here was 80 percent. The model was trained using the training dataset and tested using the testing dataset. Table 1 illustrates the specific amount of data set used in every stage. Then the train model module was dragged in and the input and output data were specified; from there, the training process started to train the model. The scored module was dragged in and the remaining 20 percent data was provided for testing and the outcome of the training can be checked in the evaluation model module. Fig.6(a) is showing the generated model. The average accuracy level for this particular model was 94.65 percent and shown in fig.8. The training module required further processing after completing all these steps. It was then set up for web service where a web service was generated and published. Fig.6(b) is showing the deployed web service generated for the trained model. Anyone can display and use this model from the Microsoft web library after deploying the trained model. The new inputs were then provided to test whether our model was able to predict and provide the perfect tensile strength or not. Table 2 displays some sample data that we used.

4.3 Assessment of model quality

Predictions are used to measure the accuracy and sensitivity of model quality. Prediction accuracy can be found by dividing the correct predictions with the total number of predictions. Sensitivity is the proportion of samples accurately predicted by class out of the total number of samples including the class. Fig.7 displays the graph plotted for both the original data and the predicted data from the model.

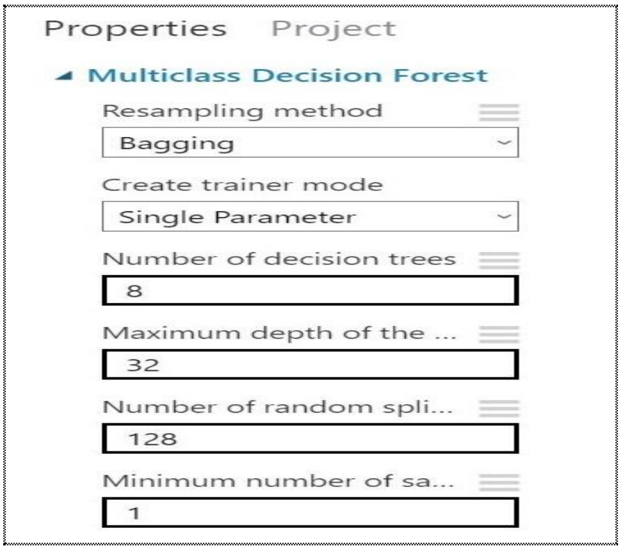


Fig.5 Hyperparameter values

Table 1 Training data.

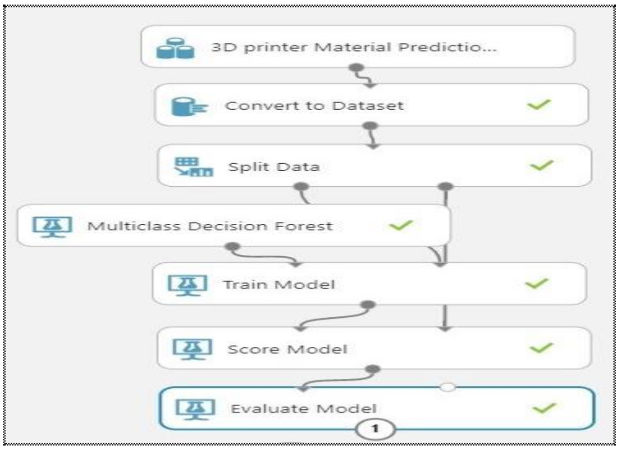
Data sets	Amount of data
Total data	60
Training data	48
Testing data	12

Table 2 Sample training data. [28]

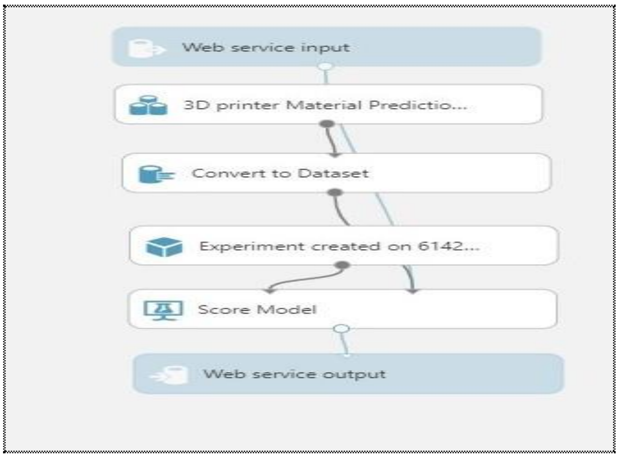
wall thickness	infill density	nozzle temperature	tensile strength
8	90	220	18
7	90	225	16
1	80	230	8
4	70	240	10
6	90	250	5
10	40	200	24

5. Implementation and approach for cloud-based optimization

Since the whole project is aimed to create an autonomous system where no or a little man-machine interaction (MMI) would be required, the first move towards that was to create a website from which customer’s orders are collected. Some features on the website will make it user friendly and easy to select which type of items to print. Now, the input data will be generated from their needs and go straight to the model developed at the Azure machine learning studio. After obtaining the input data, the generated model began to evaluate and produce an output. For feeding the data into a 3D printer, a raspberry pi module will be connected to the machine. Input and output parameters will be supplied to the machine directly from the Raspberry pi for any particular product Then the printing will be started by the 3D printer.



(a) Trained model



(b) Deployed trained model

Fig.6 Trained models

So, the purpose of using Raspberry pi is to transfer the generated output data along with the input data to the 3D printer. Product design needs to be done through computer simulation when new product orders or personalized product orders are obtained. A three-dimensional CAD design needs to be generated and given to the 3D printer through Octoprint. The design of the product and slicing will be done remotely, then product monitoring and other parameters of the 3D printer can easily be given using Octoprint. The framework of this project is shown in fig.9, where the flows for every operation is shown clearly.

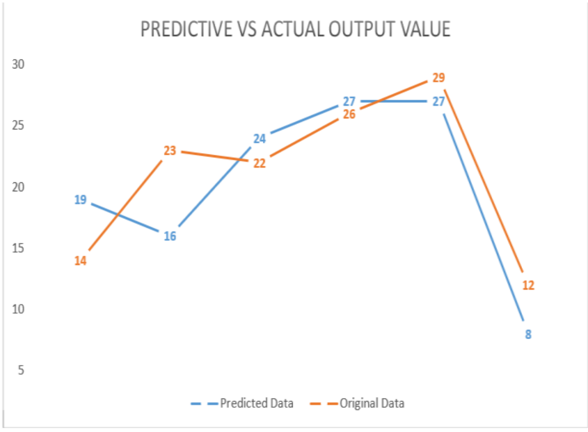


Fig.7 Difference between the predicted and actual output value

Metrics

Overall accuracy	0.277778
Average accuracy	0.946502
Micro-averaged precision	0.277778
Macro-averaged precision	NaN
Micro-averaged recall	0.277778
Macro-averaged recall	NaN

Fig.8 Accuracy level of the trained model

6. Conclusion

In this study, a framework for a fully automated Cyber-Physical System (CPS) was demonstrated using a machine learning algorithm based on a multiclass DF model. The optimization process was also conducted here in the middle of the system in the Microsoft Azure platform. A pathway for the future manufacturing industry is illustrated here. The end product contained a combination of Industry 4.0, smart manufacturing, and optimization algorithm altogether. The system comprised intelligent machining and generated an optimized final product using the elements of Industry 4.0. This can help getting the best quality product for the customer in a significantly easy way.

7. Acknowledgement

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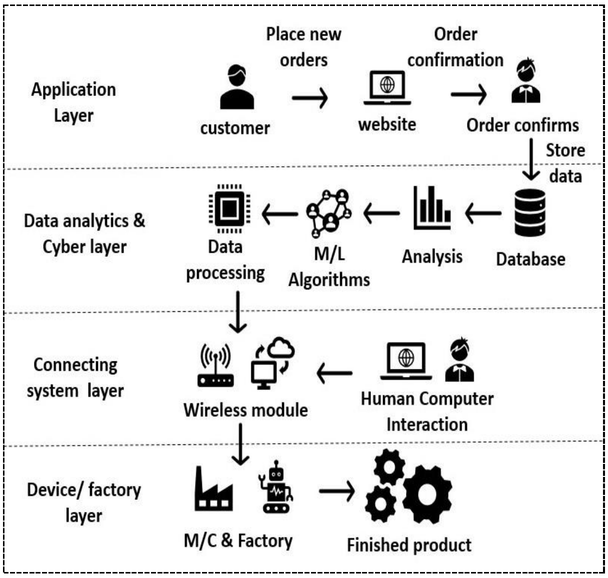

Fig.9 Framework for the proposed CPS system

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NOMENCLATURE

CPS : Cyber-Physical System
FDM : Fused Deposition Modeling
SLS : Selective Laser Sintering
IJM : Inkjet Modeling
SLA : Stereolithography
CAD : Computer-Aided Design
IoT : Internet of Things
PLA : Polylactide
DF : Decision Forest
MMI : Man-Machine Interaction
ABS : Acrylonitrile-Butadiene-Styrene