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# A Machine Learning based Frame Work for Predicting Overall Equipment Effectiveness with Environmental Factors in Additive Manufacturing

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## Abstract

*In advanced manufacturing technologies, Additive Manufacturing (AM) stands out for its potential to revolutionize production processes. However, assessing the efficiency and productivity of AM machines remains a significant challenge. This research work presents a novel framework for generating a dataset to calculate the Overall Equipment Effectiveness (OEE) of additive manufacturing machines. The proposed OEE-3D printing framework systematically captures Key Performance Indicators (KPIs) including availability, performance, and quality metrics specific to AM processes. By integrating data acquisition techniques with real time monitoring systems, the proposed framework ensures the accurate collection of relevant operational data. This work outlines the methodology, data collection procedures, validation techniques, k-nearest neighbours, support vector machine and Naive Bayes machine learning algorithms utilized for predicting the OEE values, both inclusive and exclusive of environmental parameters, pertaining to the AM machine. The findings demonstrate the capability of this methodology to yield practical insights and drive continuous improvement in the additive manufacturing sector. Correlation analysis within the study revealed strong positive relationships between availability and performance (0.99), as well as between OEE and both availability (0.91) and performance (0.89).*

**Major Findings:** *This study reveals that environmental factors significantly impact the Overall Equipment Effectiveness (OEE) in 3D printing. Specifically, fluctuations in room temperature, bed temperature, nozzle temperature, and humidity adversely affect print quality, machine performance, and downtime. By integrating sensors to monitor these conditions, we observed enhanced process stability and efficiency. Additionally, incorporating environmental factors into OEE calculations resulted in a noticeable shift from "Good" to "Moderate" performance categories, underscoring their critical role in equipment efficiency. Furthermore, predictive models like K-Nearest Neighbors (KNN) and Support Vector Machine (SVM) demonstrated high accuracy in forecasting OEE, even when accounting for environmental influences.*

**Keywords:** *Additive Manufacturing, 3D Printing, Machine Learning, Overall Equipment Effectiveness*

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## 1.0 Introduction

Industry 4.0, also known as the 4th Industrial Revolution, refers to the ongoing transformation in manufacturing and related industries through the integration of digital technologies. It is characterized by the fusion of the physical and digital worlds, facilitated by advancements in cyber-physical systems, the Internet of Things (IoT), Artificial Intelligence (AI), and big data analytics[1,2]. This revolution aims to create smart factories where machines and systems are interconnected and capable of autonomously exchanging information, triggering actions, and controlling each other independently[3].

AM faces numerous challenges that can benefit from the application of Machine Learning (ML) to enhance OEE[4]. ML techniques can optimize print parameters such as speed, nozzle temperature, and material composition to improve print quality and consistency while reducing defects. Predictive maintenance using ML algorithms can predict equipment failures based on sensor data, minimizing downtime and maximizing machine uptime[5]. Quality control in additive manufacturing can be significantly improved through ML driven defect detection and classification, ensuring that printed parts meet stringent quality standards. Additionally, ML can optimize material selection and usage, reduce waste, and enable personalized manufacturing by analyzing complex data sets and adapting production parameters accordingly[6]. These advancements highlight the transformative potential of ML in addressing critical issues in additive manufacturing, paving the way for more efficient and scalable production processes across diverse industries.

Therefore this research proposes the OEE-3DP framework for assessing the OEE of AM machines through ML techniques. This framework facilitates precise OEE by systematically gathering important performance indicators *via* real time monitoring and prediction utilising ML algorithms such as KNN, SVM and Naive Bayes algorithm. The results indicate great accuracy, with little performance fluctuations when accounting for environmental conditions. This AI based methodology facilitates data informed decision making, enhancing additive manufacturing process efficiency.

Since the industrial revolution, machine tools have been utilized extensively in manufacturing processes and have shown a considerable influence on productivity in the sector[7]. They also continue to improve their performance. The most important and desirable features of machine tool 4.0 include cyber physical machine yools, vertically and horizontally integrated machine tools, and machine tools that are safer, more intelligent, and autonomous[8]. Therefore industry 4.0 makes machine tools more intelligent, safe, dependable, and adaptable by merging vertical and horizontal integration in manufacturing facilities at the plant level. Additive manufacturing has progressed significantly, providing advantages including cost efficiency, sustainability, and personalization. Nonetheless, other hurdles hinder their widespread implementation, including as material constraints, printing precision, nozzle specifications, aggregate dimensions, and the absence of defined protocols. The incorporation of automation, robots, and digital modelling improves productivity while also presenting interoperability challenges. Maintaining accuracy, structural integrity, and adherence to regulations is essential. Future breakthroughs must concentrate on enhancing printing materials, fine-tuning process parameters, and establishing common frameworks to augment scalability and reliability across diverse applications[9]. The impact of Fused Deposition Modelling (FDM) parameters such as nozzle temperature, bed temperature, printing speed and layer thickness on the mechanical properties of Carbon Fiber (CF) and Glass Fiber (GF) Poly Ether Ether Ketone (PEEK) composites is examined. Scanning Electron Microscopy (SEM) is employed to analyze fracture characteristics and inter layer bonding quality to refine printing parameters for improved mechanical performance[10]. The optimization of additive manufacturing parameters for Poly Lactic Acid (PLA) cellular structures utilized in biomedical applications, including Orthopedic scaffolds, is analyzed. The Fused Deposition Modelling (FDM) technique is examined utilizing two lattice structures Schoen Gyroid and Schwarz Primitive emphasizing layer height, flow rate, and print speed to enhance geometrical precision and mechanical characteristics. Through the application of Full Factorial Analysis (FFA) in Minitab, optimal printing parameters were determined, revealing that the Schoen Gyroid structure possesses enhanced mechanical qualities, rendering it a preferable option for Orthopaedic scaffolds[11].

The impact of the ironing procedure on the surface texture and thermo mechanical characteristics of 3D

printed PLA is examined. A fractional factorial design is employed to examine the effects of nozzle temperature, layer thickness, print speed, and infill density on material properties. The findings indicate that ironing improves surface smoothness and uniformity, while also affecting viscoelastic qualities as storage modulus and glass transition temperature, underscoring the need for optimum printing parameters in additive manufacturing[12]. The impact of nozzle temperature on warping deformation, dimensional precision, and density in FDM-printed PLA and PLA+ components is examined. Elevated nozzle temperatures often mitigate warping and enhance dimensional precision, however material contraction may induce discrepancies. Challenges remain in extensive base areas, impacting adhesion and mechanical qualities, underscoring the necessity for additional study to refine printing conditions[13]. Using FDM, nozzle temperature, print speed, and bed temperature are examined to reduce warping in 3D-printed PLA. Warping is reduced by 200° C nozzle temperature, 15 mm/s print speed, and 27° C bed temperature. Complex interplay between process settings and material qualities continue to challenge print quality, highlighting the need for more research[14]. Reinforcing two PLA grades (4032D and 2003D) with 4 wt% Cloisite 30B nanoclay using FDM examines how printing temperature affects 3D printed PLA/clay nanocomposites. Higher printing temperatures increase elastic modulus, but PLA 4032D's exfoliated nanostructure improves it more. Nanoclay enhances thermal stability and crystallinity, however optimizing printing parameters for diverse PLA grades is difficult, requiring more material and process optimization study[15]. The influence of nozzle temperature (190° C to 220° C) on rheology and mechanical properties of Triv Calcium Phosphate (TCP)-Poly Lactic Acid (PLA) composite filaments for 3D printing is examined. To avoid agglomeration and viscosity, 15 vol% TCP is utilized, although larger concentrations could be investigated. Due to the limited temperature range, absence of *in vitro* biological performance study, and single-screw extruder, sophisticated extrusion techniques and material optimization are needed[16]. The mechanical properties of FDM PLA items are influenced by printing speed, ranging from 15 to 105 mm/s, increased speeds reduce production time and material volume, yet result in diminished hardness, surface roughness and tensile strength. Concentrating on one material and speed range restricts understanding. Further investigation is required regarding nozzle temperature, layer height and infill patterns[17].

Nozzle temperature calibration in 3D printing is evaluated through experimental and numerical methods to improve item quality and production efficiency. The impact of fan cooling and envelope temperature on actual extrusion temperature is analyzed, with data driven models corroborated by thermal camera readings for precise temperature forecasts. Limitations encompass a concentration on particular process parameters and dependence on thermal cameras, underscoring the need for additional investigation into various printer types and intricate printing settings[18]. A new method using neural network techniques is used to find the best process parameters and guess the PLA's surface finish and tensile strength in additive manufacturing. To make prediction models, a dataset is created by carefully testing different factors like printing speed, layer thickness and infill density. This makes the process more efficient and less reliant on trial and error. Some problems with this approach are that it only works with the FDM method and PLA material and the accuracy of the model depends on the quality of the information and how it is used in real life[19]. As lung-equivalent materials for 3D-printed phantoms in radiology and radiation treatment, lightweight foaming PLA filaments have been investigated into. When heated, these filaments stretch and create tiny air bubbles that allow low-density prints to be made without big air gaps inside. At 100% infill, effective densities can reach as low as 0.28 g/cm$^3$. It is looked at how the material expands at different temperatures and how to get the best printing speeds for two different kinds of 3D printers. Some problems with this method are that it only works with a certain type of PLA filament, the flow rate needs to be changed for each printing setting, and there may be differences between batches of filament and printer models[20]. The impact of layer height on printing time and surface roughness in PLA that is 3D printed using FDM is examined. With the lowest roughness at 0.05 mm and the maximum at 0.25 mm, higher layer heights produce rougher surfaces; printing time also reduces with increasing layer height. At layer heights of 0.15 mm and 0.2 mm, the best surface quality and printing efficiency are combined. The concentration on a particular material and printer is one of its limitations; additional research is necessary to have a more thorough grasp of other elements including print speed, nozzle temperature and filament quality[21].

In AM, ML techniques play a role because they can predict the OEE of printed items. Through the analysis of real time data from sensors, machine parameters, and ambient factors, machine learning models discern patterns that influence availability, performance and quality. Various ML algorithms will facilitate the optimization of print settings, the detection of errors and the minimization of downtime. Integrating machine learning with additive manufacturing promotes process efficiency, reduces material waste, and increases product reliability, resulting in data driven decision making and ongoing process enhancements. Machine learning is utilized for the intelligent analysis of environmental sensor data to improve quality assurance in FDM 3D printing. The Xception Time architecture is noted for its precision and robustness, with over 95% classification accuracy. In contrast to conventional techniques like 3D scans, sensor-based data offers a more efficient, real-time, and non-destructive solution for quality monitoring[22]. Energy data analytics is employed to predict OEE in manufacturing, with the objective of enhancing sustainability and efficiency. Energy data is utilized to evaluate OEE, rather than relying on conventional approaches that link energy usage to production performance. A state-based method discerns machine operating modes from energy trends, whereas a machine learning approach utilizes statistical energy data for OEE prediction. The findings indicate that OEE may be precisely evaluated using energy data, providing a cost effective and readily implementable method to improve machine performance and energy efficiency while promoting sustainability efforts[23]. Researchers have focused on printing parameters such as availability, performance and quality of the printed components to predict OEE of 3D printers, whereas environmental conditions remain underexplored. Despite research highlighting the impact of environmental conditions on print quality, their integration into OEE prediction models is still limited. Numerous ML approaches rely on printer specific data while insufficiently considering the effects of environmental variations on material deposition, inter layer adhesion and machine stability. The lack of real time adaptive control mechanisms and sensor based feedback systems prevents the dynamic optimization of OEE. Integrating environmental data with printer operating parameters can enhance predictive accuracy, process stability and overall manufacturing efficiency in additive manufacturing.

The present research makes significant contributions by extending beyond traditional machine-specific data to incorporate the effects of temperature and humidity on the quality of 3D-printed parts. A novel OEE-3DP dataset is developed, integrating real-time environmental monitoring with availability, performance, and quality metrics for machine learning-based OEE prediction-addressing a critical gap in prior research. Furthermore, machine learning techniques are employed to develop a predictive model that enhances process stability, precision, and efficiency in OEE prediction, paving the way for more reliable and optimized additive manufacturing processes.

## 2.0 Methodology

A novel OEE-3DP framework is proposed in this research for predicting the OEE of a 3D printer by utilizing data collected from sensors, while also taking into account the availability, performance and quality of items produced at different printer speeds. The necessary sensors integrated into the FDM 3D printer generate comprehensive datasets that are later utilized in ML models to enhance OEE in AM. The first step in this procedure involves the integration of multiple sensors, including the DHT11 temperature sensor, NTC thermometer 100k sensors and humidity sensor, which continuously monitor and collect real time data throughout the printing process. Figure 1 illustrates the 3D printers equipped with sensors designed for data collection. The status and functionality of the 3D printer are evaluated through the application of the proposed OEE-3DP dataset. Ultimately, accurate measurement methods are utilized to evaluate the OEE of the 3D printer.

The contribution to the work is structured into 5 principal stages: (1) Integration of sensors for real time data collection, (2) 3D printing with FDM technology at different nozzle speeds, (3) Calculate the percentages of availability, performance, and quality while assessing the impact of environmental factors on quality and OEE, (4) Analyze and visualize the collected dataset and (5) Validate the proposed OEE-3DP dataset using ML models.

### 2.1 Integration of Sensors for Real Time Data Collection

The incorporation of sensors for real time data collection includes the installation of multiple sensors on the 3D printing apparatus to consistently track

essential parameters including nozzle temperature, bed temperature, ambient temperature and humidity levels. Details of the sensors integrated is illustrated in Table 1. The sensors collect data throughout the printing process, which is subsequently utilized to monitor machine performance and environmental conditions. This data offers valuable insights into machine health and process efficiency, facilitating improved decision making for optimization of OEE. The following section describes the detailed information about the sensors.

### *2.1.1 DHT11 Sensor*

A DHT11 is a digital sensor integrated to 3D-printer to monitor the room and bed temperatures as well as the 3D printer's humidity in order to monitor the quality thereby efficiency. Before using the filament for printing, it is helpful to measure the humidity to prevent moisture absorption. In order to keep the early layers of the print adhering well to the build plate, the bed temperature is also checked. This reduces the risk of separation, shifting, or warping during printing, ensuring structural integrity, surface smoothness, and dimensional accuracy. Functional tests confirm the object's performance and reliability, demonstrating the potential of AM for precise and efficient production.

Equation 1 calculates the temperature from the data provided by the DHT11 sensor[24]. The integer part of the temperature is represented by the 3rd byte of the data received from the sensor, while the decimal part is stored in the 4th byte, which is typically "zero" for the DHT11 sensor.

$$\text{Temp}\left(^{\circ}\text{C}\right) = \text{Temp Integer Part} + \frac{\text{Temp Decimal Part}}{10} \quad (1)$$

### *2.1.2 Humidity Sensor*

The humidity sensor is integrated in 3D printer to measure the amount of moisture in the surrounding air while printing. Because of this, high humidity while printing can lead to problems including poor print quality, weakened material, and an increase in print failures[25].

This is especially true for hygroscopic filament materials like PLA and Acrylonitrile Butadiene Styrene (ABS). As a result, the moisture level is additionally gathered by the OEE-3DP dataset to preserve ideal circumstances for reliable and superior prints.

### *2.1.3 NTC Thermistor 100k*

Further, 3D printers incorporate the NTC Thermistor 100k temperature sensor to measure the heated nozzle's temperature. Various materials need varying nozzle temperatures to melt and flow properly throughout the printing process. By integrating this sensor for monitoring, the 3D printers are protected from overheating, which could cause under extrusion, stringing and clogging.

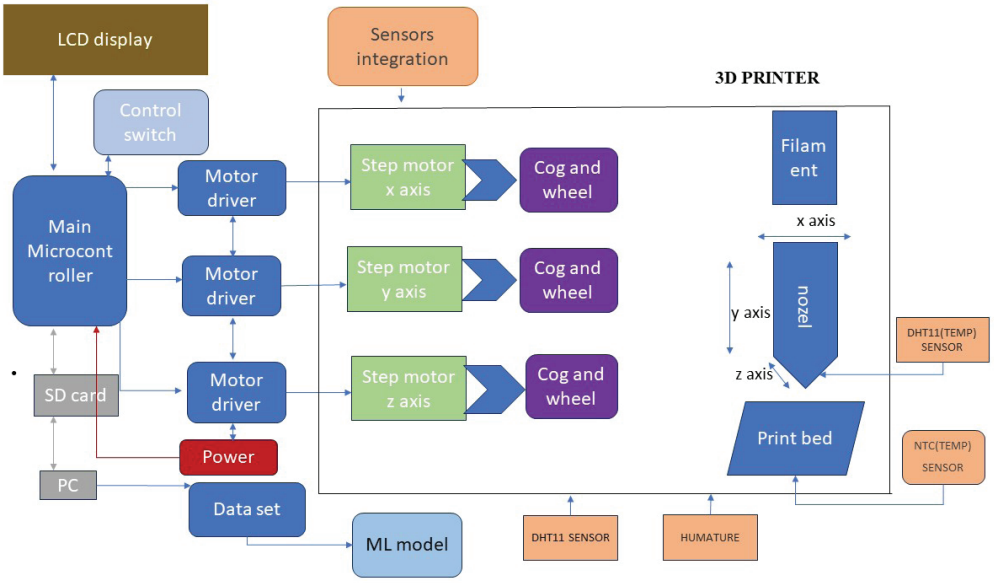



**Figure 1.** Proposed framework for the generation of OEE-3DP dataset.

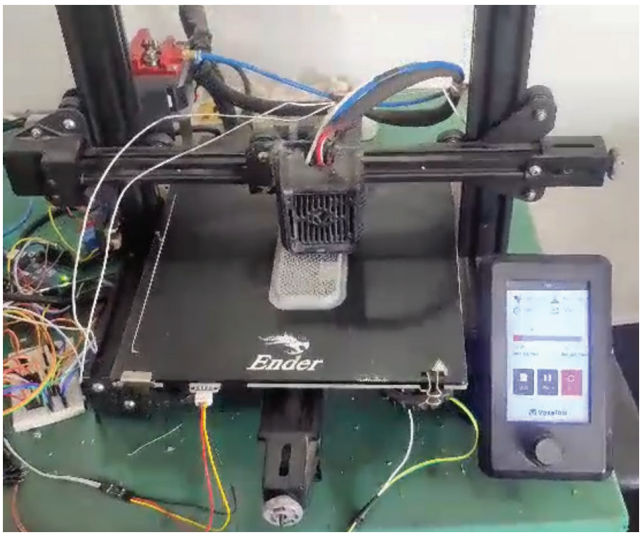



**Figure 2.** Sensors integration on FDM 3D printer.

**Table 1.** Details of the sensors used to capture real time data

| Sensor | Principle | Measurement Range | Least Count |
|---|---|---|---|
| DHT11 temperature | Polymer film's electrical response. | 0 to 50° C | 0.1° C |
| Humidity | Air thermal conductivity sensing | 10 to 90 % | 1 % |
| NTC thermistor 100k | Sintered semiconductor temperature sensing | -40 to 150° C | 0.1° C |

The printouts are as a consequence smoother and more accurate. The Figure 2 shows the sensor integrator for the generation of the OEE-3DP dataset.

The Equation 2 is a Steinhart-Hart equation for the calculation of the temperature from the NTC Thermistor 100K sensor.

$$\frac{1}{T} = A + Bln(R) + C(ln(R))^3 \quad (2)$$

where T is the temperature in Kelvin, R is the resistance of the thermistor in ohms and A, B, and C are the Steinhart-Hart coefficients specific to the thermistor.

### *2.1.4 Data Collection*

The generation of the dataset is one of the crucial parts, data collection serves as a pivotal component, particularly in the integration of sensors for enhancing operational efficiency and print quality. In this section, a methodology is proposed for the collection of data from 3D printers equipped with sensor integration, tailored specifically for enhancing the additive manufacturing process. Figure 2 illustrates the setup employed for data collection, encompassing the integration of sensors within the 3D printer environment. The infrastructure comprises two primary components: The 3D printer itself and the integrated sensor network. Through the utilization of sensors such as temperature sensors, humidity sensors, real time data is captured in various aspects of the printing process, including temperature fluctuations, humidity variation, availability of the machine, different print speed resulting in the surface quality. This data is then systematically logged and stored for subsequent analysis, aiding in the identification of trends, anomalies, and optimization opportunities within the additive manufacturing workflow.

## 2.2 3D Printing with Fused Deposition Modelling (FDM) Technology at Different Nozzle Speeds

The investigation involved all phases of the AM process, from design to quality assurance. A 3D model is initially created using Computer Aided Design (CAD) software and converted into an STL file. The model is subsequently divided into layers using slicing software (Ultimaker Cura), producing accurate instructions for the 3D printer. This software enables the customization of several parameters, including print speed, infill density, infill pattern and support structure generation, all of which affect the output quality. The set parameters are as follows: Layer height 0.3 mm, wall thickness 1.2 mm, infill density 20%, infill pattern: Lines, nozzle temperature 205° C, bed temperature 50° C, print speed 30, 50, 70, and 90 mm/s. The object was scrutinized carefully as it was produced layer by layer. The post processing encompassed cooling, removal of supports, and surface refinement. The evaluation of dimensional precision, surface finish and structural soundness was performed through quality control protocols, while the object's functionality was verified by functional testing. This study demonstrated the capabilities of additive manufacturing for accurate and efficient output.

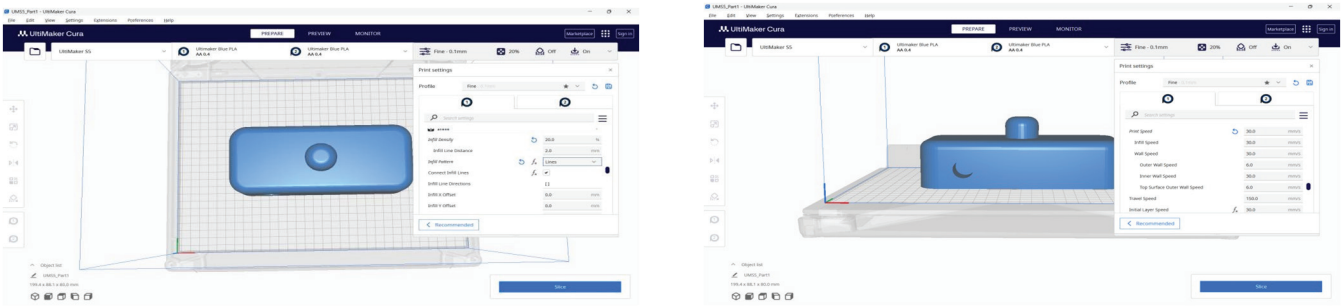
The detailed specification of the FDM 3D printer is as follows

1. Model: Ender 3 V2 which is a well-rounded 3D printer.

**Table 2.** Details of the data for OEE-3DP

| Data Set | Description |
|---|---|
| Bed temperature | Denotes the controlled temperature of the build platform during printing, which influences material adhesion and print quality. |
| Bed temperature-percentage | Denotes the bed temperature which got converted into % by taking the standard bed temperature for Ender V2 additive manufacturing machine for poly lactic acid. |
| Nozzle temperature | Refers to the controlled temperature of the printing nozzle, crucial for material flow and adhesion optimization, thereby enhancing equipment performance and productivity. |
| Nozzle temperature-percentage | Refers to the nozzle temperature which got converted into % by taking the standard nozzle temperature for Ender V2 additive manufacturing machine for poly lactic acid. |
| Humidity-percentage | Refers to the level of moisture in the air within the printing environment. |
| Room temperature | Refers to the ambient temperature of the printing environment. |
| Room temperature-percentage | Denotes the room temperature which got converted into percentage by taking the standard room temperature for Ender V2 additive manufacturing machine for poly lactic acid. |
| Speed | Refers to the velocity at which the printing head or build platform moves during the printing process. |
| Availability-percentage | Refers to the percentage of the planned production time during which the machine is actually operational and capable of producing parts. It takes into account both scheduled and unscheduled downtimes. |
| Quality-percentage | Refers to the degree to which the 3D printed parts meet specified standards, focusing particularly on surface quality and Ultimate Tensile Strength (UTS). These two parameters are critical indicators of the overall performance and reliability of the printed parts. |
| Performance-percentage | Refers to the efficiency and speed at which the machine produces parts relative to its designed capacity. It measures how well the machine adheres to the planned production schedule and speed, focusing on the actual output rate compared to the ideal or theoretical maximum. |
| OEE-percentage | OEE is a comprehensive metric used to evaluate the efficiency and effectiveness of an Additive Manufacturing (AM) machine. OEE takes into account three key factors: Availability, performance, and quality. It provides a clear picture of how well a 3D printer or AM machine is being utilized compared to its full potential. |
| Environmental factor | In this case study environmental factors such as bed temperature, nozzle temperature, room temperature and humidity took into account as these factors play crucial roles in determining the quality of the printed parts. These factors influence the printing process, material properties, and the final part's mechanical and surface characteristics. |
| Quality with environmental factor | Refers the quality of 3D printed parts by considering environmental factors such as bed temperature, nozzle temperature, room temperature and humidity. |
| OEE with environmental factor | OEE with environmental factor takes into account three key factors: Availability, quality with environmental factor and performance. It provides a clear picture of how the environmental conditions influence the quality of the parts in turn OEE of the 3D printer to its full potential. |

2. Build volume: 220 x 220 x 250 mm.
3. Printer dimensions: 475 x 470 x 620 mm.
4. Weight: Approximately 7.8 kg.
5. Layer resolution: 0.1-0.4 mm.
6. Printing speed: Up to 180 mm/s.
7. Nozzle diameter: Standard 0.4 mm interchangeable.
8. Filament diameter: 1.75 mm.
9. Maximum nozzle temperature: 255° C.
10. Maximum bed temperature: 100° C.
11. Supported filaments: PLA, Thermoplastic Polyurethane (TPU), Polyethylene Terephthalate Glycol (PETG), Acrylonitrile Butadiene Styrene (ABS).



**(a)** Parameter settings **(b)** Parameter settings

**Figure 3.** Parameter settings in ultimate cura slicing software.

## 2.3 Percentage Calculations

### *2.3.1 Bed Temperature Percentage*

For PLA, the Ender V2 3D printer suggests a bed temperature of 50° C to guarantee stability, adhesion and high quality prints[26]. On machine beds, lower temperatures increase the danger of lifting and warping. Bed temperature percentages are computed using Equation 3, emphasizing the effects of variations and the necessity of keeping the temperature at 50° C for best outcomes.

$$\text{Bed temperature percentage} = \left(\frac{\text{Bed Temperature}}{50}\right)\times 100 \qquad (3)$$

### *2.3.2 Nozzle Temperature Percentage*

The Ender V2 nozzle is set up to 180° C for PLA to facilitate smooth extrusion, enhance interlayer bonding, and achieve uniform deposition. This temperature reduces blockages, optimizes surface finish, and enhances print detail[27]. By applying Equation 4 and setting the nozzle temperature to 180° C as the standard, percentage of nozzle temperature is calculated.

$$\text{Nozzle temperature percentage} = \left(\frac{\text{Nozzle temperature}}{180}\right)\times 180 \quad (4)$$

### *2.3.3 Room Temperature Percentage*

The Ender V2 3D printer operates optimally at a room temperature of 25° C for PLA, resulting in reduced warping, enhanced adhesion, and uniform cooling. This stabilizes the temperatures of the extruder and bed, thereby preventing rapid cooling of PLA. Variations from 25° C can influence adhesion, cooling efficacy, and print longevity, establishing it as the optimal condition for dependable, high-quality prints. Equation 5 determines the nozzle temperature percentage at various instances while taking into account the usual ambient temperature.

$$\text{Room temperature percentage} = \left(\frac{\text{Room temperature}}{25}\right)\times 100 \qquad (5)$$

### *2.3.4 Availability Percentage*

The term "availability" in additive manufacturing describes the real amount of time the machine is available for printing, not including the time needed for bed and nozzle cooling and heating[28]. It takes roughly three minutes to heat the nozzle and bed of the Ender V2 3D printer to 180° C and 50° C, respectively, and 10 minutes to cool down. These periods are regarded as machine availability losses. The heating and cooling times are deducted from the total time that the software estimates to arrive at the actual printing time. As demonstrated in Table 3 for different nozzle speeds, the availability percentage is calculated by dividing the actual time by the ideal time and multiplying by 100 as shown below.

$$\text{Availability percentage} = \left(\frac{\text{Available time for printing}}{\text{Time shown by the software}}\right)\times 100 \qquad (6)$$

### *2.3.5 Performance Percentage*

The performance of an AM machine, expressed as a loss in printing speed percentage, is influenced by several factors including machine condition, material properties, environmental factors and process parameters. Issues like mechanical wear, inadequate calibration and outdated firmware can reduce efficiency[29]. Filament quality and

**Table 3.** Shows the % of availability for different nozzle speeds

| Nozzle Speed mm/ sec | Time Shown by the Software in min | Heating Time in min | Cooling Time in min | Available Time for Printing in min | Availability % |
|---|---|---|---|---|---|
| 30 | 730 | 3 | 10 | 717 | 98.21 |
| 50 | 485 | 3 | 10 | 472 | 97.31 |
| 70 | 388 | 3 | 10 | 375 | 96.6 |
| 90 | 115 | 3 | 10 | 278 | 36.72 |

**Table 4.** Shows the percentage of performance for different nozzle speeds

| Nozzle Speed mm/sec | Ideal Time Shown by the Software in min | Actual Time Taken for Printing in min | Performance % |
|---|---|---|---|
| 30 | 655 | 730 | 89.72 |
| 50 | 450 | 485 | 92.78 |
| 70 | 363 | 388 | 93.55 |
| 90 | 305 | 115 | 37.70 |

material type also affect speed, as some materials require slower printing for optimal results. Environmental factors like extreme temperatures and humidity impact filament behavior, while print settings such as resolution, layer height, and infill density directly influence speed. Complex designs and support structures further slow down printing to maintain accuracy. Understanding these factors helps optimize machine performance and reduce speed losses. Performance percentage is calculated using the Equation 7.

$$\text{Performance percentage} = \left(\frac{\text{Ideal time shown by the software}}{\text{Actual time taken for printing}}\right) \times 100 \quad (7)$$

### *2.3.6 Quality Percentage*

Accurate evaluation of the performance and dependability of printed components in 3D printing requires strict quality measurement. Surface roughness and ultimate tensile strength are crucial parameters for this assessment. Surface roughness pertains to the surface texture of a print, which impacts both its visual appeal and practicality[30]. A lower level of roughness correlates with superior quality. Indicating its mechanical integrity, ultimate tensile strength quantifies the highest stress a material can endure before fracturing. Various parameters, including layer height, printing speed and material type, exert an influence on both measurements. Table 5 illustrated the

**Table 5.** Shows the values of surface roughness and UTS at different nozzle speeds

| Nozzle Speed mm/sec | Surface Roughness (Ra micro meter) | Ultimate Tensile Strength (N/mm2) |
|---|---|---|
| 30 | 4.75 | 36.6 |
| 50 | 9.4 | 37.1 |
| 70 | 15 | 41.2 |
| 90 | 23 | 42.2 |

**Table 6.** Shows the normalised values of surface roughness, UTS and the quality percentages at different nozzle speeds

| Nozzle Speed mm/sec | Normalized Ra Score (Ra micro meter) | Normalized UTS Score (N/mm2) | Quality % |
|---|---|---|---|
| 30 | 65.90 | 66 | 65.95 |
| 50 | 76.36 | 71 | 73.68 |
| 70 | -27.2 | 112 | 42.4 |
| 90 | -100 | 122 | 11 |

results of the tensile strength tests performed using a Universal Testing Machine (UTM) and the Rubert surface roughness comparator for different speeds.

In the quality calculation, both surface quality and Ultimate Tensile Strength (UTS) have been assigned equal importance. The surface roughness and UTS normalized scores are calculated, together with the corresponding percentage of quality and are presented in the Table 6.

### *2.3.7 OEE Percentage*

For AM equipment, OEE is a crucial indicator, since it offers a detailed evaluation of the effectiveness of a manufacturing process. Therefore, three main elements are taken into account by OEE, which are performance, quality, and availability.

High OEE in AM ensures efficient operation, flaw free components and minimal downtime, leading to higher output, lower costs and better resource use[31]. It also identifies areas for improvement, essential in high precision, low volume production where consistency and quality is key[31]. It highlights gaps in previous studies that overlook these production losses. Finally, Overall Equipment Effectiveness (OEE) is calculated by using Equation 8.

Overall Equipment Effectiveness = (Availability × Performance × Quality) (8)

# 3.0 Results and Discussions

## 3.1 Effect of Environmental Fctors on Quality Percentage

Room temperature, bed temperature, nozzle temperature and humidity are critical operational and environmental factors that directly influence the quality there by OEE in 3D printing[32]. Room temperature fluctuations affect bed and nozzle stability, causing print defects and reducing OEE. Proper bed temperature ensures adhesion, preventing warping and detachment, while precise nozzle control maintains material flow, avoiding extrusion issues. High humidity leads to filament moisture absorption, lowering print quality and increasing downtime. Monitoring these factors with sensors enhances reliability, efficiency and OEE[33].

Applying Lean manufacturing to 3D printing emphasizes continuous improvement, addressing challenges like temperature control and isolation in biofabrication. Sensor integration enables real-time monitoring, ensuring process stability and efficiency. This approach improves quality, reduces waste, and enhances productivity, offering scalable solutions from academic labs to industrial settings.

In this research work we considered 40% for the nozzle temperature, 30% for bed temperature, 20 % for room temperature and 10% for humidity. By taking these percentages for different sensors calculated the environmental effect on the quality of the part printed. Equation 9 and Equation 10 illustrates how to calculate the OEE and quality of the printed parts by taking the environmental factors into consideration along with the crucial printing parameters.

Overall Equipment Effectiveness = (Availability × Performance × Quality) (9)

Quality_Env factor = ((0.4× percentage of nozzle temperature) + (0.3 × Bed temperature percentage) + (0.2 × Room temperature percentage) + (0.1 × humidity percentage)) (10)

### 3.1.1 OEE with Environmental Factor

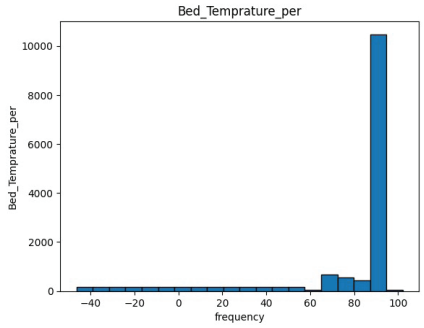
Environmental factors like temperature and humidity impact OEE in AM by affecting print quality, machine performance and downtime. Monitoring these conditions enhances process stability and efficiency. Equation 11 is used to calculate OEE with environmental factors.

OEE with Environmental Factor = (Availability × Performance × Quality_Env factor) (11)

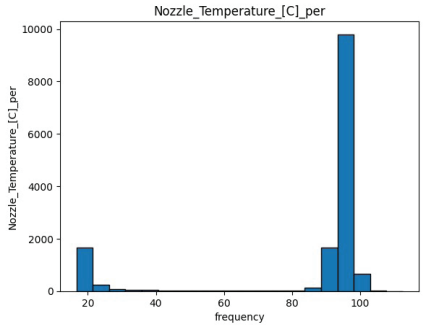
### 3.1.2 Dataset Analysis and Visualisation

To optimize the OEE of the Ender V2 3D printer, a detailed data analysis and visualization procedure has been performed. This research focuses on a merged dataset containing a variety of sensor data and performance metrics collected at different nozzle speeds. The dataset encompasses both environmental conditions such as room temperature and humidity and machine specific parameters like bed temperature, nozzle temperature, speed, availability, performance, and quality. The goal of analyzing this vast amount of data is to find important patterns that can lead to enhancements in the machine's productivity and output quality.

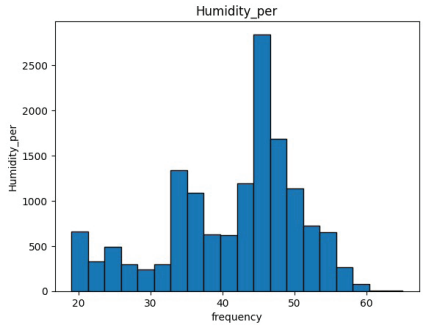
Visualizing the OEE-3DP dataset helps identify key patterns affecting OEE in 3D printing, enabling predictive modelling and data driven improvements. This ensures optimal Ender V2 performance and high quality prints by refining ambient conditions and operating settings. Sensor data from a 3D printer at various nozzle speeds (30, 50, 70, and 90 mm/s) is analyzed to evaluate availability, performance and quality, leading to OEE calculation. Environmental effects on part quality were also assessed, refining the OEE. The continuously generated dataset, with around 5000 rows per speed,



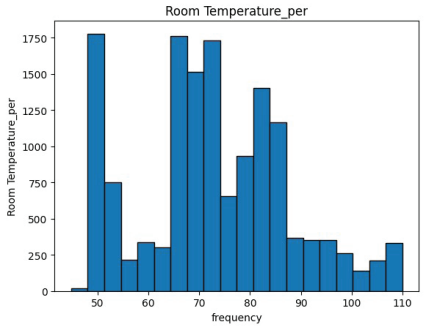

**(a)** Bed temperature frequency



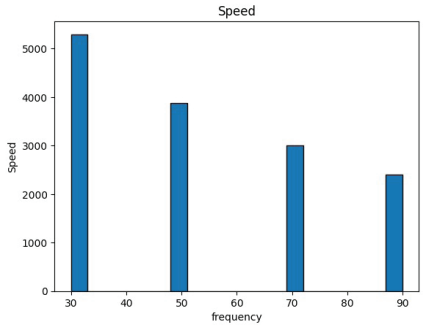

**(b)** Nozzle temperature frequency



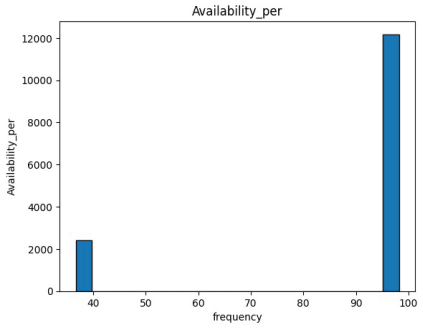

**(c)** Humidity frequency



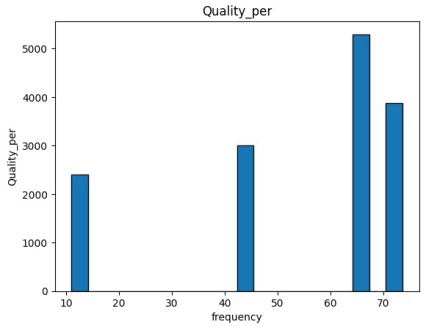

**(d)** Room temperature frequency



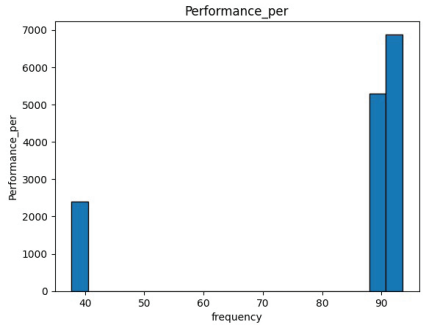

**(e)** Speed frequency



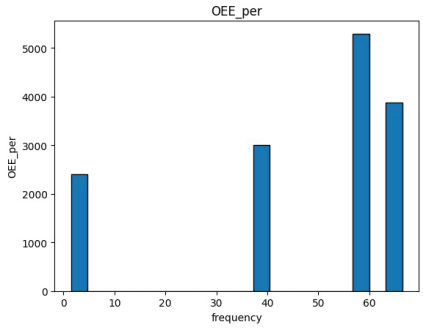

**(f)** Availability frequency



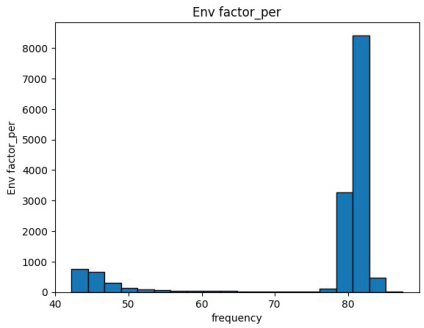

**(g)** Quality frequency



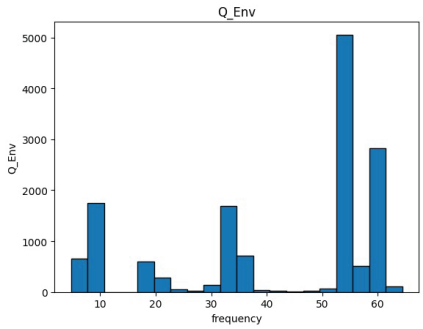

**(h)** Performance frequency



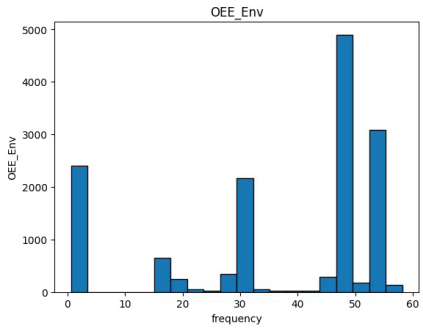

**(i)** OEE-percentage frequency




**(j)** Environmental factor frequency

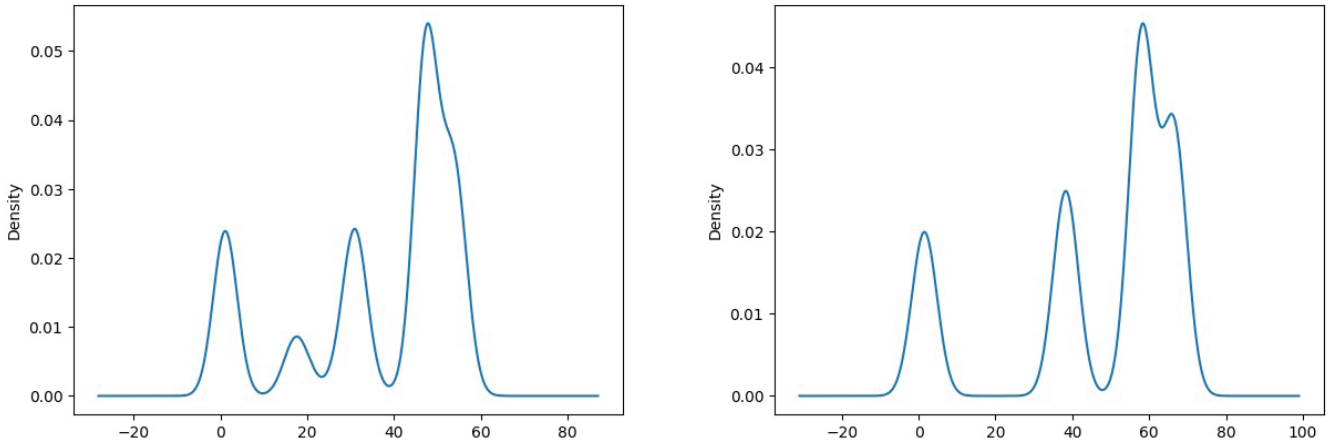



**(k)** Q-Environmental factor frequency




**(l)** OEE-environmental factor frequency

**Figure 4.** Frequency of different parameters in dataset.




**(a)** OEE_per **(b)** OEE_Env

**Figure 5.** Density plots for OEE with and without environmental factors.

was processed in Python for comprehensive analysis and visualization.

Further OEE percentages are categorized into four ranges: Bad (0-30), Moderate (30-50), Good (50-75), and World Class (75-100), and tallied the occurrences within each category. The same categorization and counting were also applied to OEE with environmental factor values. Frequency of different parameters of the dataset has been plotted and shown in the Figure 4. A visualizing parameter distribution helps to identify correlations between environmental factors and machine performance. Insights, such as optimal temperature ranges for high quality prints, guide future settings for improved output. These visualizations clarify machine behavior, ensuring optimal operating conditions.

### *3.1.3 Density Plots*

The distribution of OEE categories in two scenarios without taking environmental elements into account (on the left) and with consideration of environmental factors (on the right) is shown in Figure 5. "Good" accounts for the bulk of instances in the first chart, with "moderate", and "bad". This shows that most data points show respectable performance when environmental influences are ignored, but rare instances of the greatest performance levels (world class) are present.

There is an evident shift in the second chart, which includes environmental elements. With fewer examples in the "good" category, the "moderate" category has the greatest total. This shows that when environmental factors are taken into account, fewer examples fall into the "good" category, emphasizing the influence of environmental factors on performance. In all cases, there are hardly any entries in the "World Class" category, illustrating how difficult it is to reach the top performance levels. These charts highlight the importance of environmental factors in the precise determination and classification of equipment efficiency.

### *3.1.4 Correlation Heatmap*

Figure 6 illustrates the relationships among several characteristics associated with 3D printing, including bed temperature, nozzle temperature, humidity, room temperature, speed, availability, quality, performance and OEE. The color scale denotes the magnitude and orientation of these relationships, where dark blue signifies robust positive correlations, dark red signifies robust negative correlations, and lighter shades suggest lesser correlations.

First and foremost robust positive correlation (0.99) between availability and performance, indicating that when availability rises, performance also tends to rise. Likewise, the OEE exhibits a robust positive relationship with both availability (0.91) and performance (0.89), therefore underscoring the significance of both aspects in enhancing the overall efficiency of the equipment. Conversely, speed exhibits a robust inverse relationship with OEE (-0.85), performance (-0.69), and quality

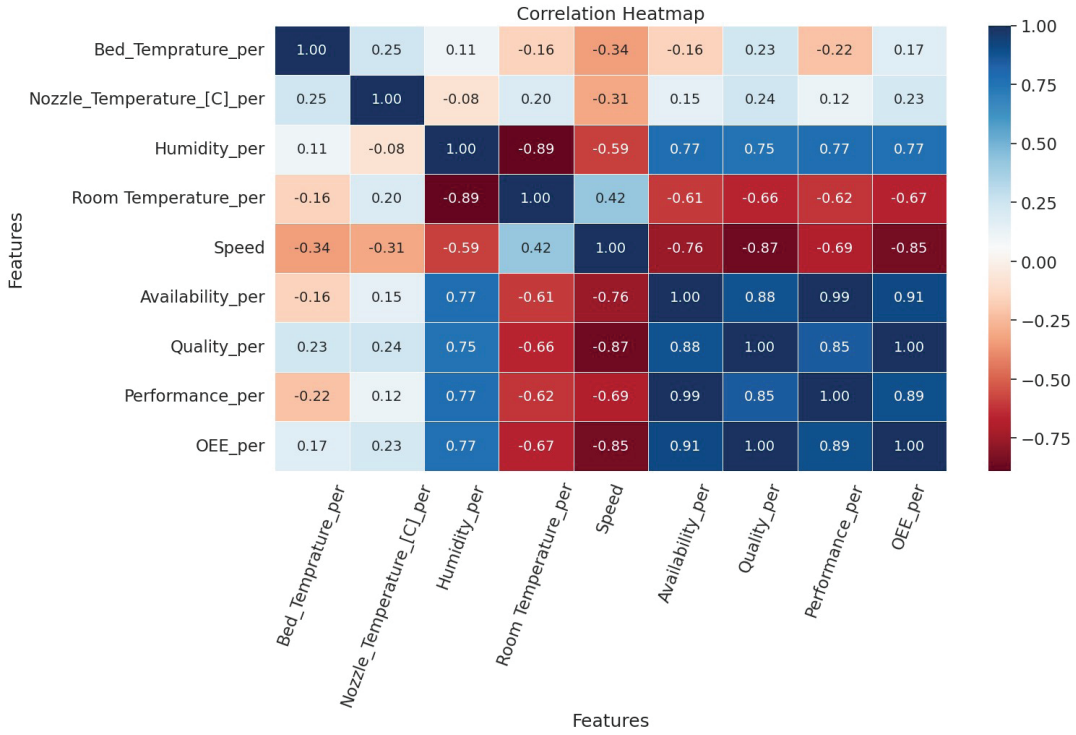



**Figure 6.** correlation heatmap.

(-0.87), suggesting that increased speeds could potentially undermine these factors.

Room temperature and humidity exhibit a strong negative correlation (-0.89), suggesting that variations in one may have an inverse impact on the other. Significantly, there exists a positive association between humidity and both availability (0.77) and quality (0.75), indicating that regulation of humidity could potentially contribute to the improvement of these objectives.

Overall, heatmap in Figure 6 illustrates the interdependent relationship between various variables in 3D printing, with some factors such as availability, performance, and OEE being strongly correlated, while others, such as speed, may have a detrimental effect on these important results. Gaining a comprehensive understanding of these connections is essential for maximizing the efficiency of 3D printing operations.

### *3.1.5 Pair Plot*

Pair plot depicted in Figure 7 provides a thorough understanding of the ways in which different parameters, including vibration, speed, room temperature, humidity, bed temperature, and nozzle temperature (in degrees Celsius), interact with one another to affect the surface quality in 3D printing. Every variable is plotted along the axes, accompanied by color coding to denote varying surface quality levels and scatter plots that display pair wise correlations between them. The diagonal elements of the plot clearly display each variable's distribution, making it simpler to understand how these variables vary across different levels of surface quality. It is clear which combinations of variables are linked to better or poorer surface quality outcomes by looking at the clustering and distribution of colors in the scatter plots.

Figure 7 highlights the impact of bed and nozzle temperatures on surface quality, emphasizing the need to consider both operational parameters like speed and environmental factors such as humidity and room temperature. Given the complex interactions between these variables, optimizing surface quality requires a systematic approach. The pair plot serves as a valuable tool for identifying key factors and their correlations, aiding efforts to refine the 3D printing process for improved results.

### *3.1.6 Effect of Environmental Factors on Distribution of OEE Categories*

Figure 8 illustrates the distribution of OEE categories, both in the absence and presence of environmental

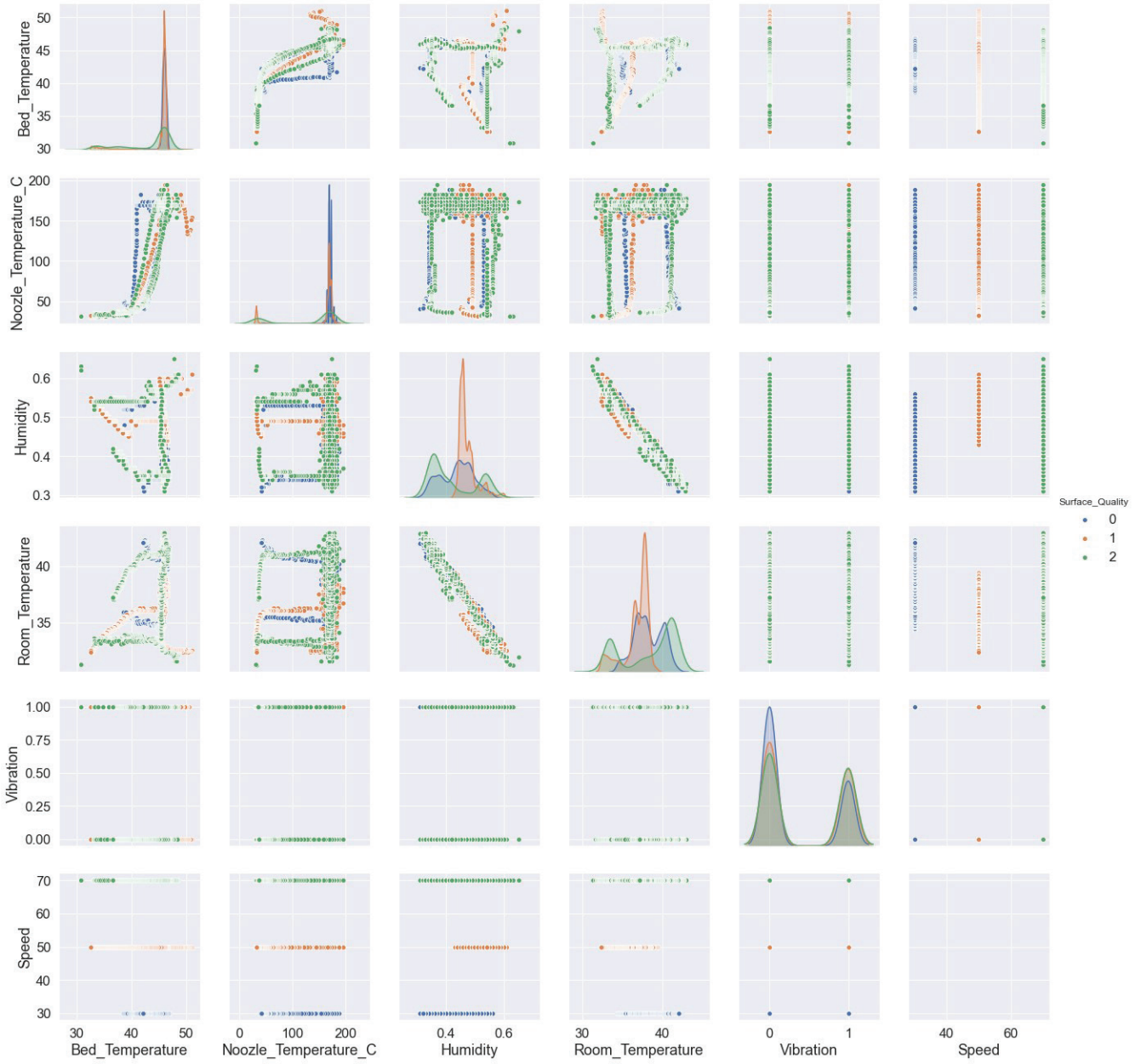



**Figure 7.** Pair plot.

factors. The graphic on the left displays the category distribution without environmental parameters, of which the "Good" category stands out with the largest count, surpassing 9000. The "Moderate" and "Bad" categories exhibit decreasing data counts, with "Bad" having the lowest frequency of occurrences. The OEE-3DP dataset does not include any entries in the "World Class" category, which usually signifies the highest level of performance, without taking into account environmental requirements.

A significant change is shown on the right side of the category distribution with environmental parameters chart. Presently, the "Moderate" group has the largest number, surpassing 7000, indicating that environmental conditions exert an impact on the categorization of performance. The "Good" group comprises a far less number of occurrences in comparison to the left chart, suggesting that environmental factors have a negative impact on the classification of what was previously regarded as "Good". The percentage of the "Bad" category

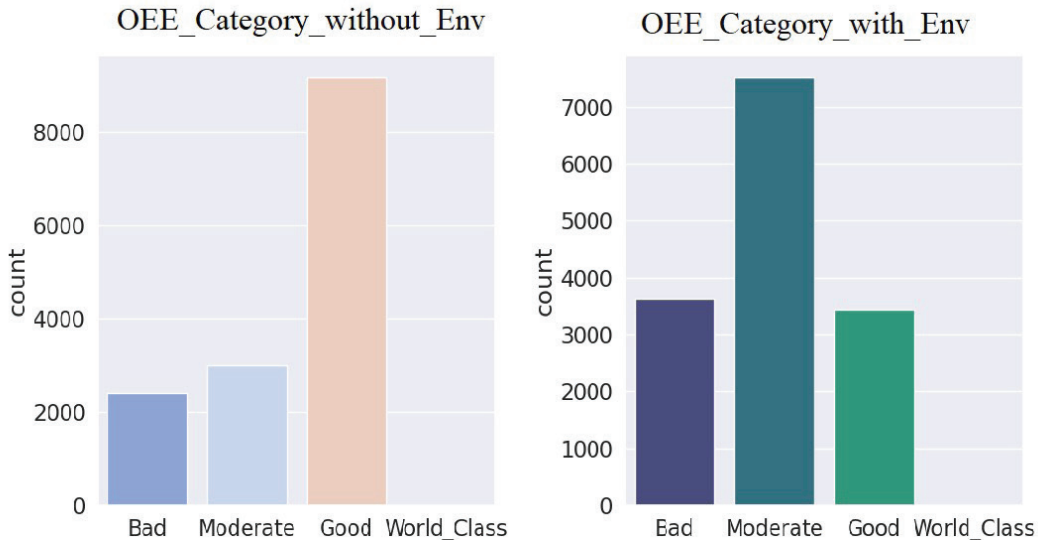



**Figure 8.** Effect of environmental factors on distribution of OEE categories.

is rather constant in both maps, although it is somewhat more in the version that includes environmental influences. "World Class" category is absent from both charts. Overall, the inclusion of environmental factors seems to decrease the incidence of "Good" ratings while substantially augmenting the occurrence of "Moderate" classifications. These findings indicate that the performance of equipment can be influenced by ambient factors, resulting in reduced overall efficiency. Gaining insight into this transition can assist 3D printing industries in enhancing OEE of the printers by considering environmental dimensions that were previously neglected.

K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Naive Bayes play a crucial role in forecasting OEE, both with and without environmental factors[34-36]. KNN, a non-parametric, instance based learning algorithm, effectively classifies data based on proximity to known patterns and demonstrates high accuracy in OEE prediction when environmental influences are excluded. SVM, which classifies data by determining optimal hyperplanes, also achieves flawless performance in this scenario, indicating that operational parameters alone distinctly define OEE trends. Naive Bayes, a probabilistic classifier based on Bayes theorem, assumes feature independence and, despite slightly lower accuracy, remains valuable for OEE forecasting. When environmental factors are considered, KNN and SVM maintain strong performance, while Naive Bayes provides probabilistic insights into their impact on OEE fluctuations. Table 7 and 8 indicate that, without environmental considerations, KNN and SVM achieved 100% accuracy; precision, recall, and F1 score, while Nave Bayes scored slightly lower with 99.03% accuracy, but still demonstrated strong predictive ability. However, incorporating environmental factors led to a slight reduction in model performance, with KNN achieving 99.62% accuracy, SVM 99.39%, and Naive Bayes 97.31%. The observed decline in precision, recall, and F1 score

**Table 7.** OEE percentage prediction without environmental factors into consideration

| Model | Accuracy % | Precision % | Recall % | F1 Score % |
|---|---|---|---|---|
| KNN | 100 | 100 | 100 | 100 |
| SVM | 100 | 100 | 100 | 100 |
| Naive Bayes | 99.03 | 98.58 | 99.41 | 98.58 |

**Table 8.** OEE percentage prediction with environmental factors into consideration

| Model | Accuracy % | Precision % | Recall % | F1 Score % |
|---|---|---|---|---|
| KNN | 99.62 | 99.70 | 99.54 | 99.62 |
| SVM | 99.39 | 99.53 | 99.24 | 99.38 |
| Naive Bayes | 97.31 | 97.11 | 97.64 | 97.34 |

across all models suggests that environmental factors introduce additional complexity in OEE prediction, highlighting their significance in understanding machine performance patterns.

## 4.0 Conclusion

This research introduces the novel OEE-3DP dataset and framework, providing a systematic approach for evaluating OEE in AM by capturing key performance indicators such as availability, performance and quality. Through real time monitoring and data acquisition techniques, the framework ensures accurate collection of operational data, allowing manufacturers to identify bottlenecks, improve machine utilization, and enhance production quality. Machine learning models including KNN, SVM and Naive Bayes were employed to predict OEE values, both with and without environmental factors, providing valuable insights into machine performance. The results indicate that while KNN and SVM deliver high predictive accuracy, Naive Bayes offers probabilistic insights into the effects of environmental variations on OEE. Incorporating environmental factors introduced additional complexity, slightly reducing model performance, yet reinforcing the importance of considering external influences in OEE assessments.

In future the OEE-3DP dataset will be expanded to include world class OEE categories, enabling manufacturers to benchmark their performance against industry leading standards. Further improvements will focus on real time adaptive control mechanisms and sensor driven monitoring systems to dynamically adjust machine parameters for optimized efficiency. Additionally, advanced AI techniques will be explored to enhance predictive accuracy and automated decision making, driving continuous improvement in AM processes.

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