A VISION-BASED QUALITY CONTROL MODEL FOR MANUFACTURING SYSTEMS

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Alejandra Figueroa-Lopez

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Kouroush Jenab
Director of Thesis

Master's Committee: ____________________________, Chair
Kouroush Jenab

____
Ahmad Zargari

____
Nilesh Joshi

____
Date

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Alejandra Figueroa-López
Morehead State University, 2021

Director of Thesis: ____
Kouroush Jenab

Production machines are essential for the manufacturing industry because of their ability to produce high-quality work in less time. Having defective products can lead to a production shutdown and economic losses for the customer. Therefore, the machines require routine maintenance checks and tools replacement. The use of a machine vision system to inspect products produced by manufacturing systems (i.e., Flexible Manufacturing Systems, Cellular Manufacturing Systems), can help improve the quality of the product. Vision systems make an important contribution to the manufacturing sector and have become an essential tool for automated assembly verification and inspection operations because of speed, accuracy, and repeatability. In manufacturing systems, a vision system can inspect hundreds of products with high precision. Vision inspection may be used in conjunction with statistical process control methods to check critical measurements and analyze trends in these measurements. By using these methods, interventions can be made to adjust the process before any defective product is manufactured.

Accepted by: ______________________________, Chair

Kouroush Jenab

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Ahmad Zargari

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Nilesh Joshi

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CHAPTER 1: INTRODUCTION

1.1 Background

1.1.1 Manufacturing

Manufacturing is a process where raw material is transformed into a final product using different tools, human labor, and machinery. These processes can be manual, simple, elaborate or they can involve the intervention of machines and new technological advances.

By observing the things that are around us, it can be seen countless finished products, like a cellphone, a car, a computer, or just a simple desk. All of these products have to go through many processes before they can reach our hands, this is possible thanks to manufacturing. Some of the most important manufacturing industries are as seen in Figure 1.

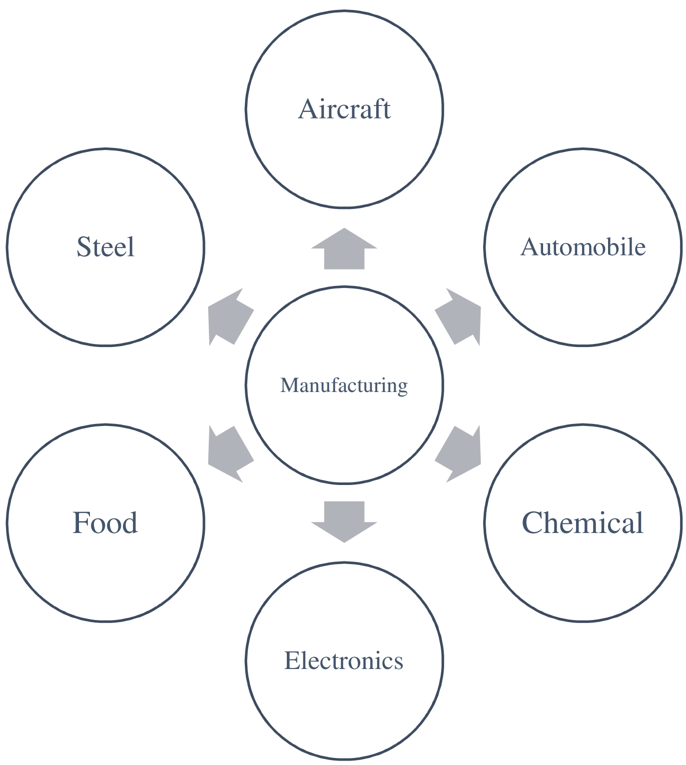

Figure 1. Manufacturing industries.

1.1.2 History of manufacturing

Manufacturing processes arose with the beginnings of humanity, since in those times, man-made use of his manual force to elaborate different types of objects that would help him survive; like crafts, which during the Middle Ages was the main economic activity.

The industrial revolution that began in England around 1780, and that later spread to Europe, North America and the rest of the world, contributed to the modernization of manufacturing processes. This period marked the transition from human labor technology into machinery manufacturing processes. Since, prior to this event, all manufacturing was done by hand.

1.1.3 Manufacturing systems

Manufacturing systems are the different processes of transformation and production of raw material through the use of tools, machinery, energy and work. These systems are fundamental in society to manufacture products or parts, efficiently and with quality.

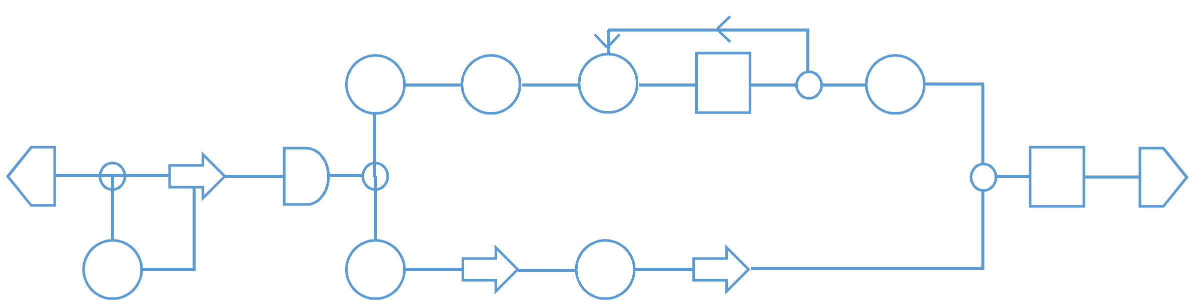

Figure 2. Process operation chart. (Montgomery, 2013)

Types of manufacturing systems

Manufacturing systems are classified into two categories: continuous and discrete.

Continuous process

In this type of process, the product goes through an assembly line from one machine to the next to make a finished product. In this process, there are no interruptions between the stages of production. An example of this process are the food, beverage (Figure 3), paper, and electronics manufacturers.

Figure 3. Beverage manufacture. (Plex, 2021)

Discrete process

This type of process produces components that can be counted as products, whose properties may be acceptable or not acceptable, according to their quality. An example of this type of process are the production of automobiles, smartphones, and aircraft, Figure 4.

Over time, products became more complex while the demand and prices increased notably. This led to an improvement in the manufacturing process and production machines, Figure 5. To respond to the demand, manufacturing systems have been equipped with multipurpose production machines.

Figure 4. Aircraft assembly. (Assembly, 2020)

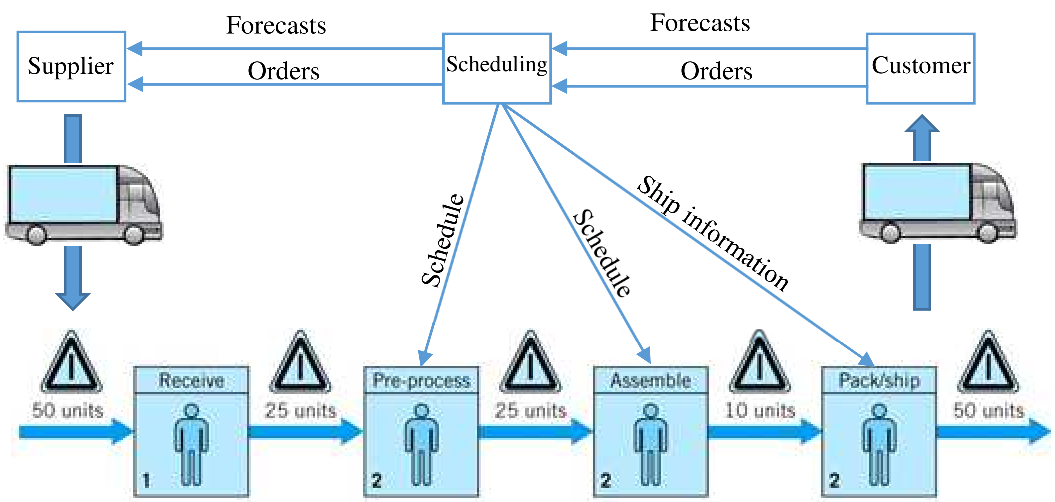

Figure 5. Demand and pricing process. (Montgomery, 2013)

Consequently, the manufacturing process is being perfected more because experience and expertise have been accumulated within each stage. Which has contributed to the reduction of production costs and manufacturing times, in addition to providing higher quality products.

Currently, from the most advanced industrial sectors to the most traditional ones, they have incorporated production machines, benefiting from advantages such as saving operation time with automatic tool change, few accidents because of reduced operator involvement, less-required operator training, flexible and versatile processes.

There are several factors that manufacturing companies cannot control, such as production shutdowns, operational costs, and raw material expenses. Therefore, they must focus on having control over their process for continuous improvement in quality, efficiency, and cost reduction. Although it is impossible to predict when a production machine will break down, a short, consistent checklist and long-term preventive plan can help reduce the risk of production shutdowns.

1.1.4 Vision systems

One of the technological tools that can provide assistance in the long-term plan of maintaining a production machine´s function is a vision system. Vision systems play an essential role in automated assembly verification and inspection operations, Figure 6. These systems have the ability to guide material handling equipment to position products as needed in a given process. Previously, quality inspectors had to individually touch and check each product as it came off the line and decide, based on their experience, whether the product meets the standard or not. Now products can automatically go from assembly to inspection, where the vision system examines each side of the product, searching for defects with incredible precision.

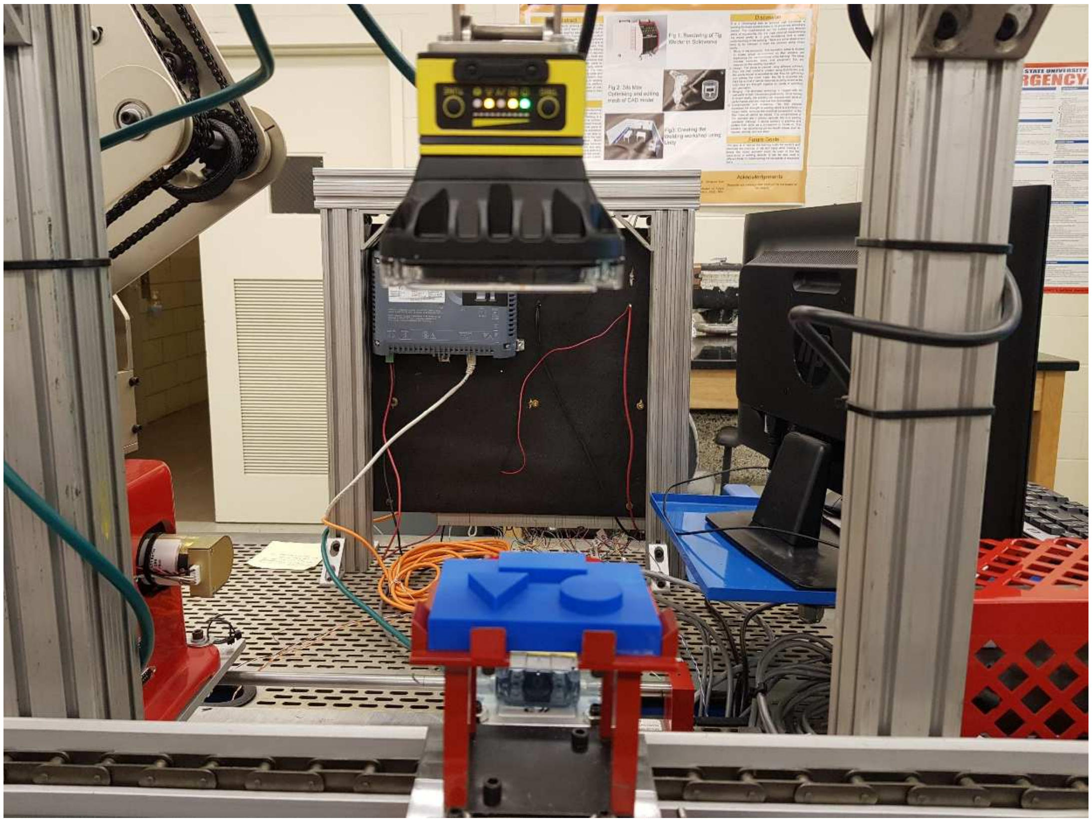

Figure 6. Vision system configuration.

Manufacturers use automated machine vision systems instead of human inspectors because they are faster, more objective, and work continuously. One of the advantages of these systems is that they can inspect many products per unit of time, providing more consistent and reliable results than the ones obtained by human inspection.

These systems work by performing under parameters programmed by the user based on specific features (distance, angle, length, etc.), which must be numerically analyzed and compared with the standard values for a particular product.

1.1.5 Statistical process control

With statistical process control (SPC), a company can move from detection-based to prevention-based quality controls. Vision systems can use different techniques or methods that are part of the SPC to detect critical changes in the performance of the process. Such performance can be monitored in real-time, allowing the operator to detect trends or changes in the process. As a result, the manufacture of defective products and waste of raw materials can be avoided.

A control chart used to monitor the mean of a process is the moving average control chart. With the data obtained during the inspection of the features (diameter, angle, length) of products, a moving average control chart will be elaborated. The mean of the process will be monitored, based on samples taken by the process at a given time. By using a control chart, a manufacturer can predict when it is time to perform maintenance to the production machines, which results in avoiding the production of defective products and incurring the unnecessary raw material cost, Figure 7.

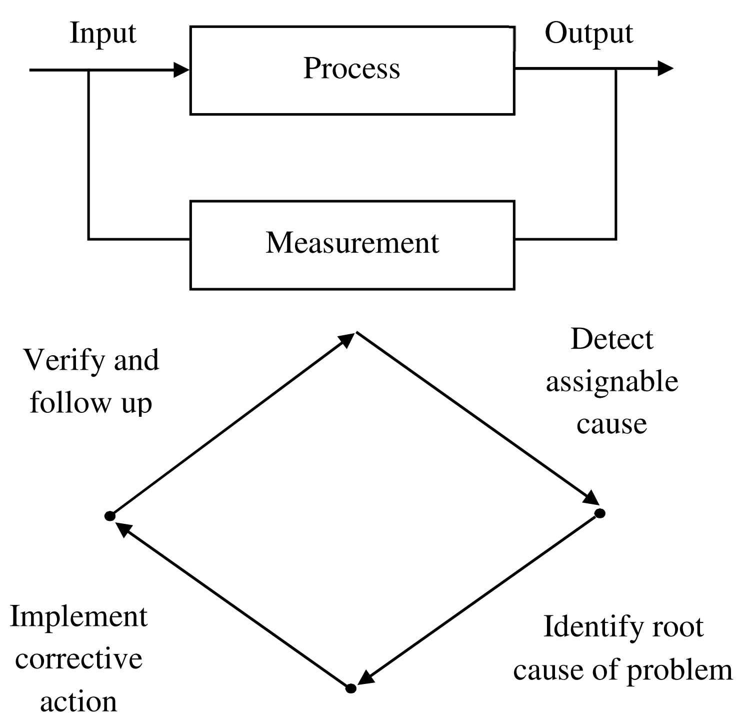

Figure 7. Process improvement.

1.2 Purpose of research

Nowadays, customers expect higher quality from manufacturers. As user expectations have risen, manufacturers have responded by emphasizing achieving consistent quality results. With the use of vision systems in conjunction with statistical process control methods, the performance of a process can be evaluated, and adjustments can be made on time. Previous work has focused on early detection of tool wear to reduce scrap, rework, overtime and costs while simultaneously increasing productivity and customer satisfaction.

The purpose of this thesis is to design a model that makes use of quality methods within a vision control system to inspect different features (diameter, angle, length) of test products and collect the resulting data from elaborating a moving average chart. After analyzing the data, the consequent prognosis and diagnosis can be used to determine when a production machine will require tool replacement in order to avoid having defective products to reduce economic losses such as raw material and production shutdown.

1.3 Research objectives

The main objectives of this research are as follows:

- Implement a vision system in the quality models (Control Charts and Tool Wear Chart).
- Predict when a production machine requires tool replacement, based on data collected during the inspection.
- Analyze moving average charts to make prognosis and diagnosis to ensure the quality of the products.

1.4 Significance of research

Manufacturing technology becomes more sophisticated every day. Now, manufacturing operations are being supplanted by faster and smarter automated devices, such as vision systems. These systems are replacing the labor force in production lines because they complete a number of tasks faster and more efficiently than human inspection ever could.

The model design for this research can be a valuable tool for training in the area of quality. By using a vision system along with SPC methods, analysis can be carried out to make decisions over the performance of a process.

As a result, the moving average chart will allow informed decisions regarding timely tool replacement and early detection of tool wear in production machines. The overall purpose is to ensure the quality of manufactured products.

1.5 Limitations

To be able to do an inspection with a vision system, it is necessary to have real products in order to obtain better results. Many products are needed for review to have enough data to be collected to establish the moving average control chart, which will evaluate the performance of the process.

1.6 Definition of terms

Automation is a technique, method, or system of operating or controlling a process by highly automatic means, as by electronic devices, reducing human intervention to a minimum.

Control Limits are the lines (horizontal) above and below the center line that are used to determine whether a process is out of control. The upper and lower control limits are based on the random variation in the process.

Defective if it has one or more defects, which are nonconformities that are serious enough to significantly affect the safe or effective use of the product (Montgomery, 2013).

Inspection is when one or more product characteristics are measured or tested and the results are compared to confirm compliance.

Manufacturing is the fabrication or assembly of components into finished products on a fairly large scale, by the use of manual labor or machinery.

Mean is the sum of the numbers in a data set divided by the number of values in the set.

Moving average charts can be used to decide whether a process is in statistical control and for detecting shifts in the process mean. Each point on a moving average chart combines information from the current sample and past samples. These charts are more sensitive to small shifts in the process average (Figure 8).

$$M_i = \frac{x_i + x_{i-1} + \cdots + x_{i-w+1}}{w}$$ **Equation 1**

$$V(M_i) = \frac{1}{w^2} \sum_{j=i-w+1}^{i} V(x_j) = \frac{1}{w^2} \sum_{j=i-w+1}^{i} \sigma^2 = \frac{\sigma^2}{w}$$ **Equation 2**

The three-sigma control limits for M_i are:

$$UCL = \mu_0 + \frac{3\sigma}{\sqrt{w}}$$ **Equation 3**

$$LCL = \mu_0 - \frac{3\sigma}{\sqrt{w}}$$ **Equation 4**

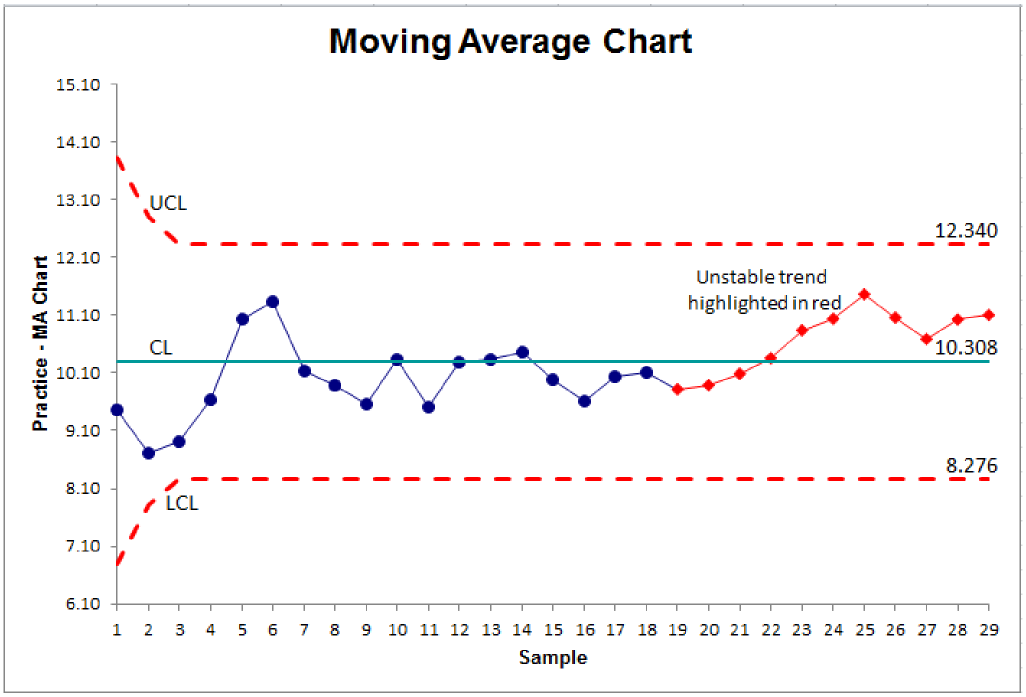

Figure 8. Moving average chart. (QI Macros, 2021)

Quality of a product can be described and evaluated in several ways. The eight components or dimensions of quality are as follows: performance, reliability, durability, serviceability, aesthetics, features, perceived quality, and conformance to standards (Montgomery, 2013).

Quality control is a procedure intended to ensure that a manufactured product adheres to a defined set of quality criteria or meets the requirements of the client or customer.

Standard value is a value that is defined as a reference point.

Standard deviation is a measure of how dispersed a set of data is in relation to the mean.

Statistical Process Control (SPC) is the use of statistical problem-solving measures to improve the quality of products or processes. SPC is mainly employed in on-line production. It brings a new dimension of defining the process, controlling it, and improving it (Pham and Oztemel, 1996).

Variance is the measurement of how far each number in a data set is from the mean.

Vision system is a combination of hardware and software that provides operational guidance to devices in the execution of their functions based on the capture and processing of images.

CHAPTER 2: LITERATURE REVIEW

2.1 Production machines

Production machines have been incorporated into different industrial sectors because of their high level of precision and accuracy in the manufacture of different types of products, Figure 9. Unfortunately, it is difficult to be able to accurately predict when a machine will wear out and present mechanical failures.

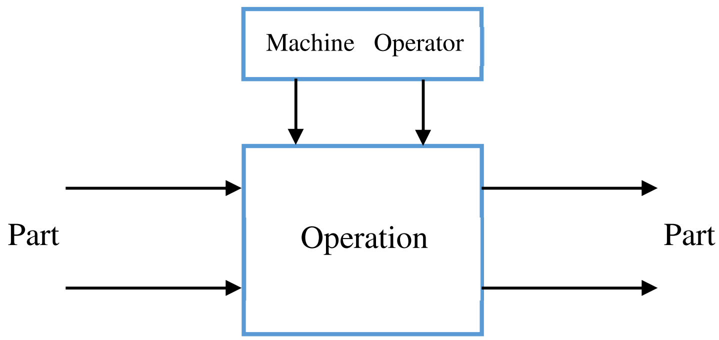

Figure 9. Input and output from the production machine.

2.1.1 Tool wear monitoring

During the cutting process (Figures 10, 11, 12), the tool suffers mechanical stresses and high temperatures. The combination of these factors determines the life of the tool, either due to the progressive wear that is produced in the contact areas between chip-tool and between part-tool or by the sudden fracture of the tool.

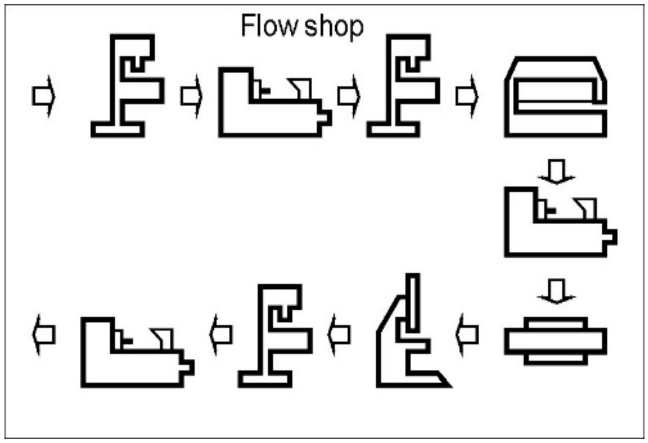

Figure 10. Product layout.

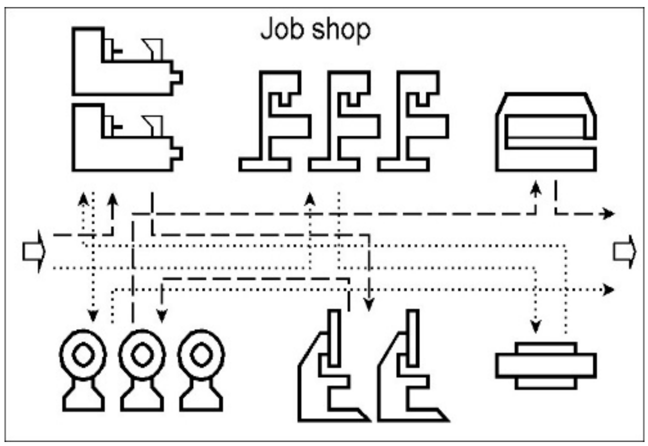

Figure 11. Process layout

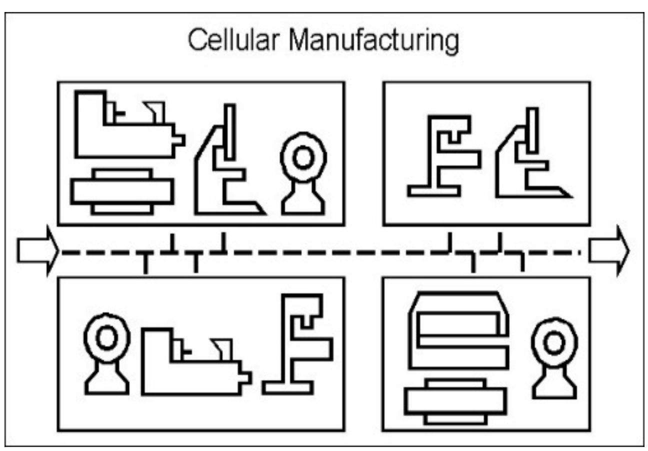

Figure 12. Cellular layout

Mechanical or thermal failures can be caused by improper use of cutting parameters or by an erroneous operation of the machine. When this rupture occurs, the tool will be immediately useless, which affects the manufacturing costs both for the tool itself and for the process stop time to replace it.

There is some research about tool wear monitoring during machining using different approaches. A research by K.J., Lee, T.M., Lee and Yang (2007) demonstrated that tool wear could be monitored by aspects of feed-rate override controlled in real-time with tool wear signal extraction through the hybrid approach to cutting force regulation. In another research, a solution to the problem in monitoring and forecasting the remaining cutting tool durability is presented. The authors developed a diagnostic module/CNC system to diagnose and predict cutting tool wear (Martinova, Grigoryev, and Sokolov 2012).

In another research, Klancnik, Ficko, Balic, and Pahole (2015), presented a new approach to monitoring of end mill tools on CNC milling machine tools with the use of computer vision and machine learning. By developed algorithms, the captured image is segmented, and the features describing individual tool teeth in the image are extracted (Figure 13).

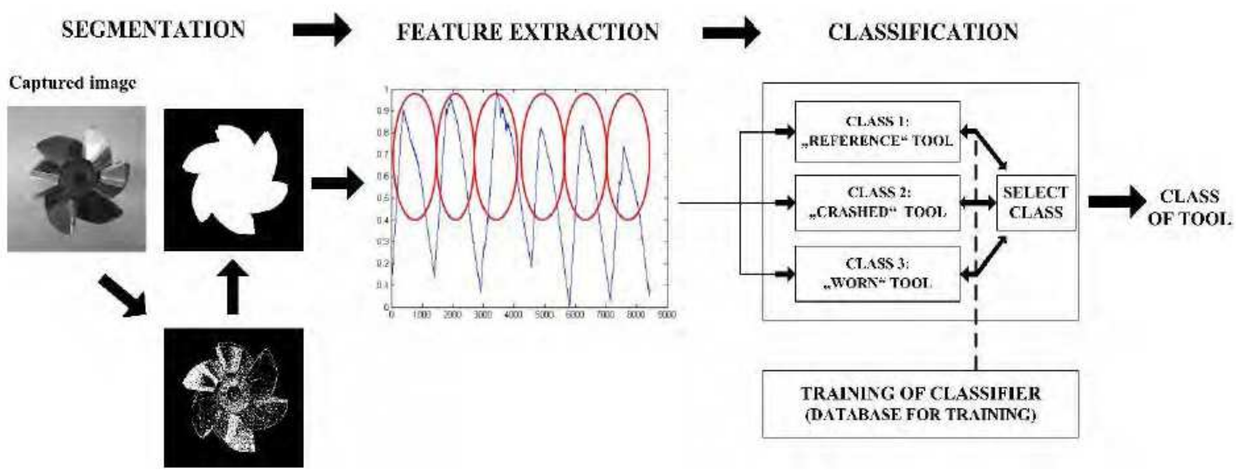

Figure 13. Computer vision-based approach for wear of end mill tool classification. (Klancnik et al., 2015)

In the research conducted by Zaujec, Vopat, Simna, and Jurina (2018) about the wear of ball nose end mill for two different coatings, it was found out that thickness and type of coating had a significant effect on the flank wear of the tool in correlation with the Ra surface roughness parameter.

Monitoring tool wear on CNC machine tools on time, will allow higher performance of these machines. Early tool wear detection will also prevent the manufacture of defective products and avoid waste of raw material. A research by Tangjitsitcharoen and Lohasiriwat (2018) proposed an in-process tool wear monitoring system regardless of the chip information in CNC turning by utilizing Daubechies wavelet transform (Figure 14). One of the advantages of their research is that the tool wear can be predicted during the cutting without stopping the machine.

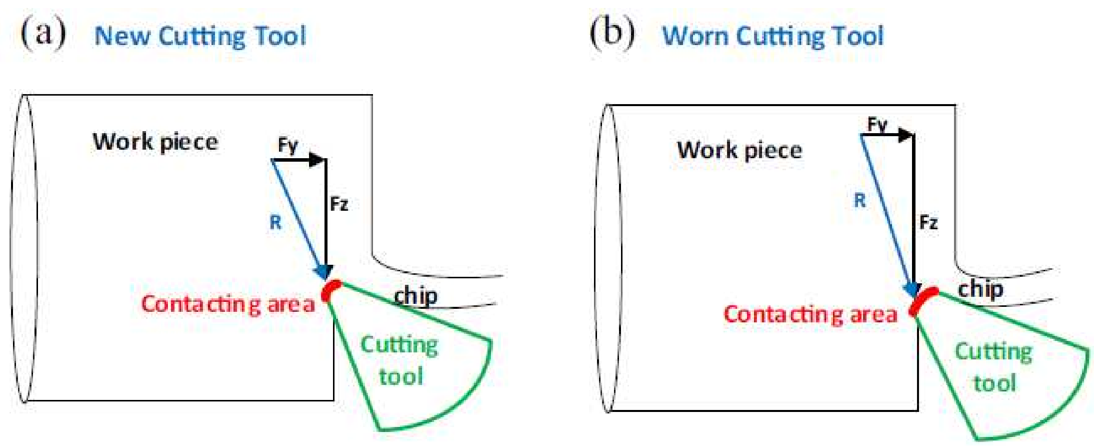

Figure 14. Contacting area between the cutting tool and workpiece. (Tangjitsitcharoen and Lohasiriwat 2018)

In another research, a fused smart-sensor was developed to quantitatively estimate the flank-wear area inserts for machining processes. In order to diminish the error in the flank-wear area estimation, the authors proposed a simple weighting function based on the product of the current and vibration signals alongside the machining parameters (Trejo-Hernandez, Osornio-Rios, Romero-Troncoso, Rodriguez-Donate, Dominguez-Gonzalez and Herrera-Ruiz 2010).

2.2 Vision systems

2.2.1 Tool wear inspection

Companies are incorporating more sophisticated technology to their processes, such as vision systems. These systems allow companies to increase production in less time, reduce raw material waste and avoid the manufacture of defective products.

Haggren (1987), defined machine vision as the use of devices for optical non-contact sensing to automatically receive and interpret an image of a real scene, in order to obtain information and/or control machines or processes.

Several studies on computer vision systems based on image processing for the measurement of tool wear have been conducted. Research by Selvaraj, Balasubramani, Hari Vignesh, and Prabakaran (2013) designed an image processing tool (MATLAB software) to determine the amount of wear accumulated on a single-point cutting tool after successive machining operations. Tool wear was estimated by comparing the gray scales of the images.

In another study, a machine vision system was developed for the direct measurement of flank wear of carbide cutting tool inserts (Figure 15). Average tool wear width, tool wear area, and tool wear perimeter are measured using the machine vision system. An average error of 3% was found for measurements of all 12 carbide inserts (Thakre, Lad, and Mala 2019).

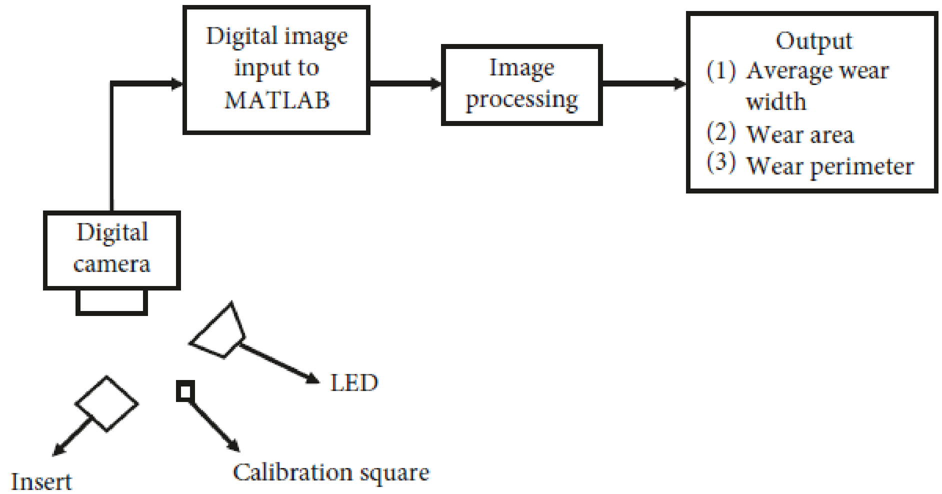

Figure 15. Schematic diagram of the tool wear measurement system. (Thakre et al., 2019)

Al-Kindi and Zughaer (2012) developed a technique to overcome problem areas associated with acquiring a measure of surface roughness assessment using vision data. The technique is designed to face the problems associated with irregular light reflection and color variation of metal work parts.

According to Kerr, Pengilley, and Garwood (2005), cutting tools must be periodically checked for possible or actual premature failures. The author´s research has demonstrated that computer vision techniques can be used successfully in a manual measurement process of flank wear estimation on both turning and milling machine tools.

Garcia-Ordás, Alegre, Gonzalez-Castro, and Alaiz-Rodríguez (2016), presented a new approach to monitor tool wear in edge profile milling operations using computer vision. The authors classify the insert according to its wear stage as a function of the wear region shape with a machine learning classification model. They used B-ORCHIZ, a shape-based descriptor computed from the wear region image.

2.2.2 Quality control

Besides monitoring tool wear on CNC machines, vision systems are also used to solve quality control problems in manufacturing processes. Manual inspection can be time-consuming and lead to human error. Therefore, it is necessary to consider automating the quality control of the products by using vision systems.

Some research has been done with vision systems in different manufacturing processes, like Ng et al., (2011), where they use an integrated approach, combining a computer vision system (CVS) and a real-time management system (RTMS), to solve quality control snag in the manufacturing of lighting products (Figures 16 and 17).

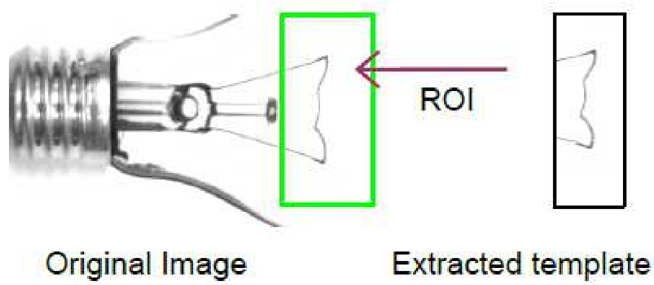

Figure 16. Example of an extracted template. (Ng et al., 2011)

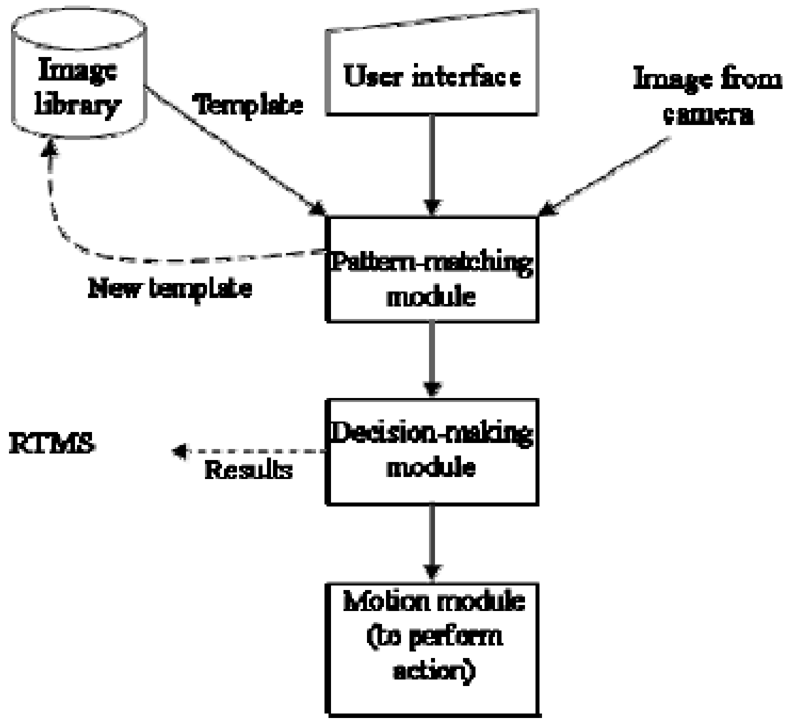

Figure 17. System architecture. (Ng et al., 2011)

Vision systems can inspect products in assembly lines and easily detect defective parts manufactured. The detection on time can avoid having raw material waste and achieve product quality. A research conducted by Santores Martínez, Gómez Ortega, Gámez García, Sánchez García, and Estévez (2013), presented a machine vision system, with an easily configurable hardware-software structure, for surface quality inspection of transparent parts, such as headlamp lenses.

Automobile industries demand high-quality inspection during the process of manufacturing. Research by Zhou, Chen, Huang, Liu, J. Yu, and X. Yu (2019), designed and implemented an automatic inspection system (AIS) for automobile surface defects that are located in or close to style lines, edges, and handles. The detection process was carried in a closed laboratory environment (Figure 18). In order to eliminate the presence of natural light irradiated on the vehicle body.

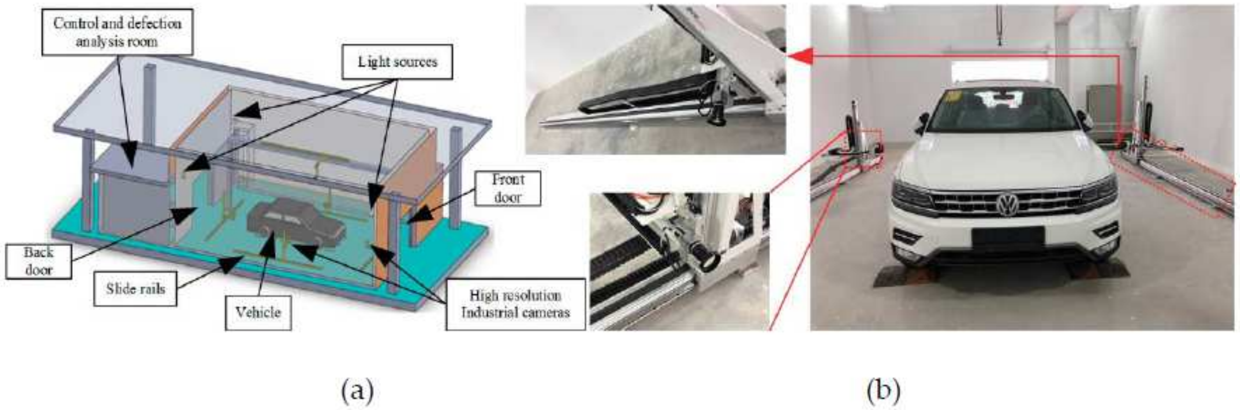

Figure 18. Laboratory of the vehicle inspection system. (a) sketch of the vehicle inspection laboratory. (b) The actual experimental scene. The camera is installed on 3-axis robot aluminum arms which are motor-driven by slide rails. (Zhou et al., 2019)

There are some manufacturing processes that are still using visual inspection, such as the surface quality of an electroplated deposit. Inspectors in charge of this task have to be with vast experience, in order to avoid having defective products. Some authors have found a solution for this, like Byrne and Sheahan (2005), who automated the inspection of surface quality through the application of inline vision systems. They evaluated three vision system types by using attribute repeatability and reproducibility analysis (ARR). The results proved that the high-speed color system achieved the highest resolution reliability output for defect identification.

Welding processes are essential for the automotive industry. High-quality welding is essential for the safety and integrity of the structure and resistance of vehicles in a collision. For this reason, operators must examine the welds after the job is finished, which requires extra time that does not always guarantee a defect-free weld. Therefore, the use of a vision system guarantees a higher quality of the weld seam and a considerable reduction in production times. A research by Herakovic, Simic, and Trdic (2010) presented a machine-vision system consisting of a mathematical algorithm developed for accurate measurement of the diameter and roundness of welded rings, to be used along with physical measurements. The results prove that using the machine-vision control system for the measuring process of the welded ring improves the overall accuracy and reliability of the results.

For Chu and Wang (2016), the measurement of the welding bead and the following evaluation of the weld quality is an important part in industrial welding. For this reason, they developed a new image processing algorithm for autonomous identifying the feature point for dimensions measurement (Figure 19) and finding out that the weld bead dimensions obtained are highly satisfactory and the weld defects are detected online.

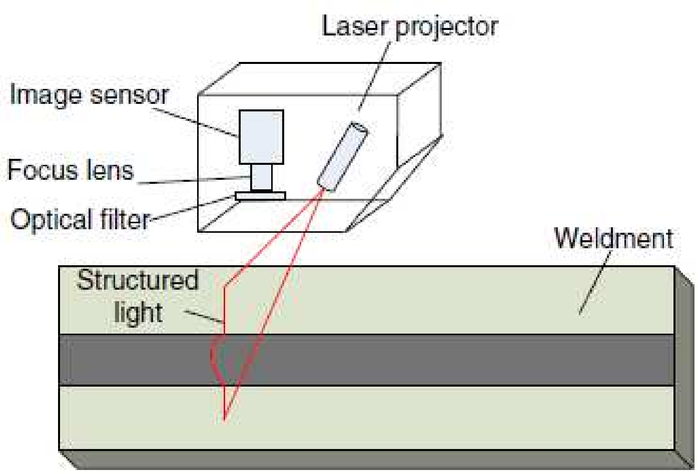

Figure 19. Diagram of laser sensor vision. (Chu and Wang 2016)

2.3 Statistical process control SPC charts

An industrial process is subject to a series of factors of random character that make it impossible to manufacture two exact same products. In other words, the characteristics of the manufactured product are not uniform and show variability. This variability is clearly undesirable, and the objective should be to reduce it as much as possible or at least keep it within limits. Statistical process control (SPC) is a useful tool to achieve this second objective. Since its application is at the time of manufacture, it can be said that this tool contributes to improving the quality of manufacturing. It also allows increased knowledge of the process, which in some cases can lead to improvement of it.

The use of statistical process control has resulted in a more comprehensive understanding clear of the behavior of a process and, therefore, obtaining solutions more successful for the control of production processes, like Tangjitsitcharoen and Boranintr (2013) where they developed in-process monitoring and SPC of the surface roughness during the turning process by using the cutting force ratio (Figure 20).

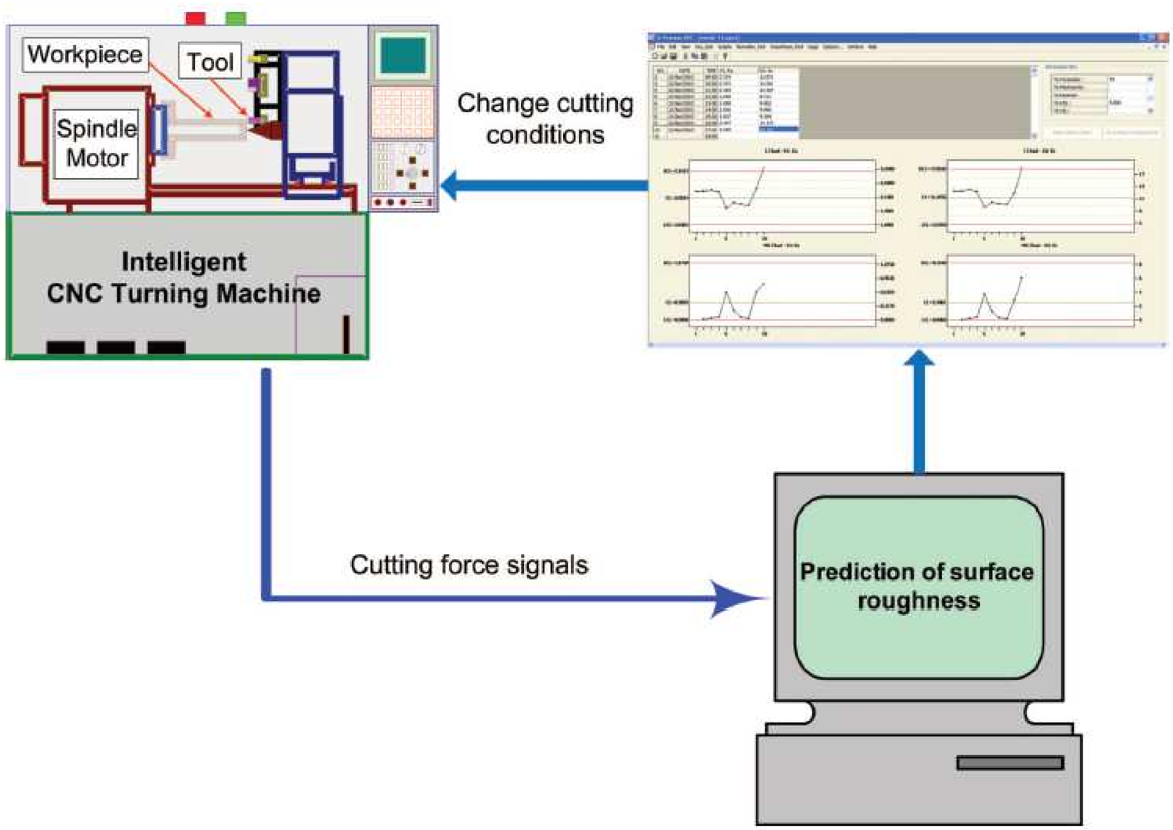

Figure 20. Illustration of the user interface between the in-process surface roughness prediction and the in-process SPC. (Tangjitsitcharoen and Boranintr 2013)

In another research a three-stage approach was proposed for the purpose of extracting the fusion feature, monitoring the health degradation (Figure 21), and optimizing the CMB strategy for motorized spindles (Figure 22) (Du et al., 2020).

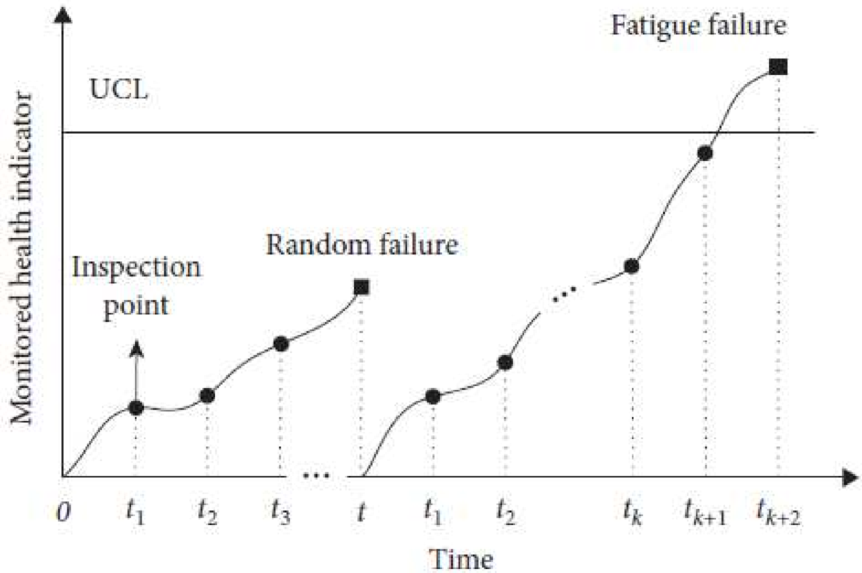

Figure 21. The SPC chart scheme of motorized spindles. (Du et al., 2020)

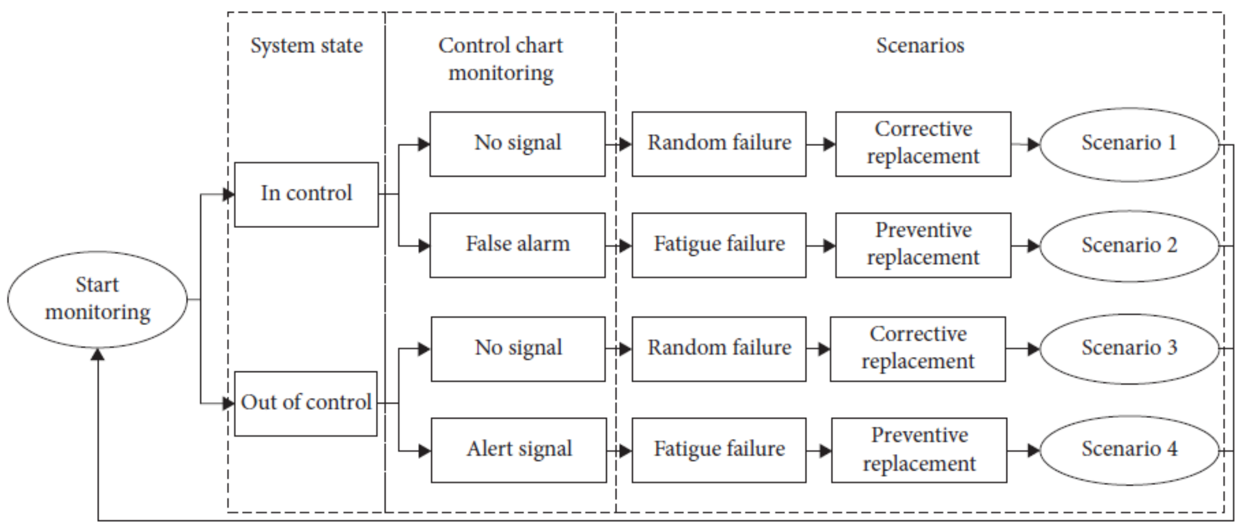

Figure 22. Four possible scenarios of the integrated CMB model. (Du et al., 2020)

For Kuzmicki and Sidorchik (2017), the algorithm of comparison is one of the major components in the system of technical vision for quality control. The authors developed an algorithm for the comparison of shots of a current video to a given template. The algorithm can be used to perform tasks such as checking the availability of the necessary components, reading the text and barcodes, size measurement, alignment check, as well as detection of defects.

Control charts are statistical process control tools that are used to monitor process parameters. The R and S charts are the most used charts to monitor process variability. Both charts are easy to implement and effective in the detection of large shifts but slow in detecting shifts of small magnitude in the process variability. (Adeoti and Olaomi, 2016). Therefore, a solution for detecting small shifts of the process mean is the exponentially weighted moving average (EWMA) control chart, like the one proposed for Sheu and Lin (2003) called the generally weighted moving average (GWMA) control chart. The authors used simulation to evaluate the average run length (ARL) properties of the EWMA control chart and GWMA control chart. They found out when quality-failure cost is expensive and where there is no permission for defective products, GWMA is suitable for monitoring the process mean.

In another research, it was proposed a newly-mixed control chart called the Exponentially Weighted Moving Average-Moving Average Chart (EWMA-MA) to detect the mean change in a process underlying symmetric and asymmetric distributions (Sukparungsee, Areepong, and Taboran 2020).

CHAPTER 3: METHODOLOGY

3.1 Conceptual design

This research was designed to attempt to predict the optimal moment for tool replacement in production machines. A model is designed to inspect within a vision system, several patterns in every product and to determine whether the product is within the range limits or not.

With the data collected in each inspection, a moving average control chart is elaborated to analyze the performance of the process and to predict when the next tool replacement can be held, in order to avoid having defective products.

The research will be divided in two stages, as seen in Figure 23, the first one is for production parts simulation. Twenty samples are inspected with the vision system to simulate the performance of the process when the tool is near to wear. In the second stage, data is collected from the inspection results to elaborate the control charts of production. First, the products are going to be designed in SolidWorks. The design will have different figure shapes to be able to do the inspection with the vision system. After the design is completed it will be printed in the 3D printer. Once the products are ready, a program will be elaborated with the In-sight explorer software. The program will inspect each product and measure the train patterns which are: diameter, angle and length, and will compare them to the standard values assigned. During the inspection, data will be collected in an excel file to elaborate a moving average and tool wear control chart. Finally, the charts will be analyzed to make a diagnosis on the performance of the process and to determine the optimal time for tool replacement.

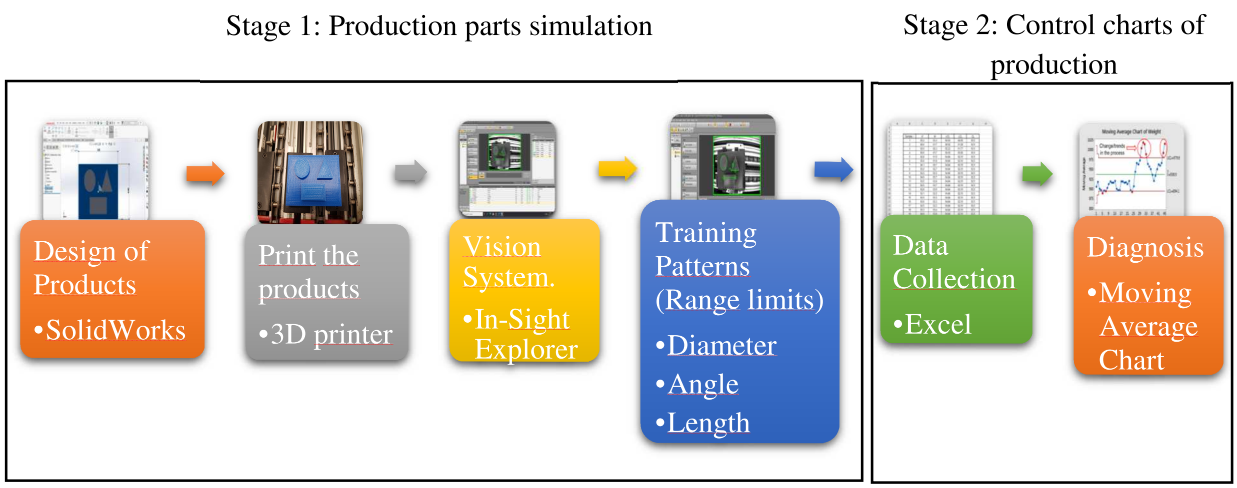

Figure 23. Methodology process.

3.2 Vision systems

3.2.1 How vision systems work

These systems are a set of components that are designed to use information from digital images to guide manufacturing and production operations, such as quality control processes.

A typical function of vision systems is for product inspection. A sensor detects if a product is present in a certain location. If there is indeed, the sensor will trigger a camera to capture an image, and a light source to highlight key characteristics of the product. Then, a digitizing device takes the camera´s image and converts it into digital output, to finally be stored in computer memory, so it can be manipulated and processed by software.

3.2.2 Vision systems components

Vision systems include the following elements shown in Figure 24.

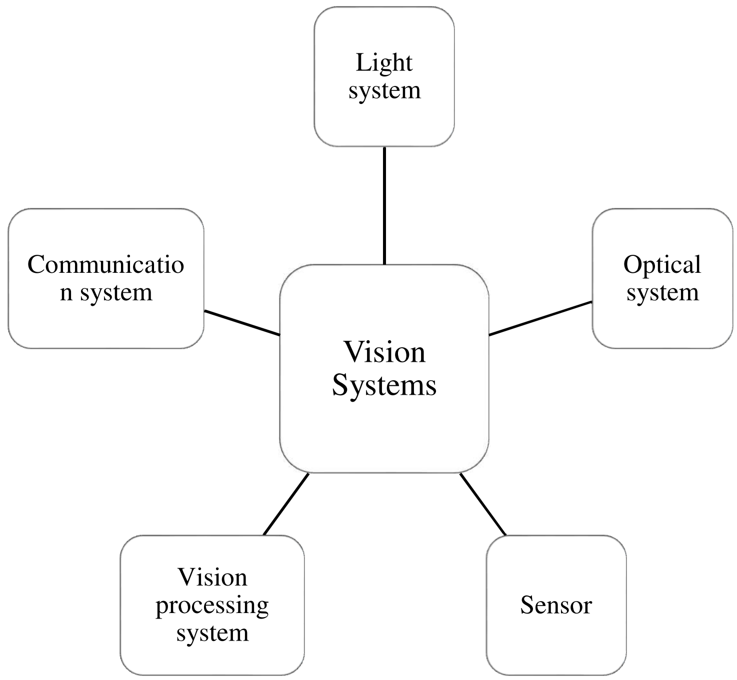

Figure 24. Vision systems components.

3.2.2.1 Lighting

The light is selected for maximizing the contrast of the features of interest to be measured or inspected while minimizing the contrast of all other features of the product, Figure 25. Parameters such as, amount of light used (intensity), style of lighting, and the placement of the light source are crucial to identify and measure the part feature being monitored.

3.2.2.2 Optical system

The optical components are commonly a lens or a camera, which integrates the lens with other elements, such as the sensor. The lens will determine the depth of focus and the focal point, which will relate to the ability to observe features of the parts being inspected by the vision system, Figure 26. The selection of the lens is dependent on the specific function being performed by the system and by the dimensions of the feature under observation.

Figure 25. Lighting in vision systems (Cognex, 2021).

Figure 26. Optical system in vision systems (Cognex, 2021).

3.2.2.3 Sensor

The sensors serve to capture the light from the optical system and convert that into a digital image. Sensors use CMOS or CCD technology to convert the captured light into a set of pixels that show the presence of light in the areas of the original parts being inspected. Sensors with higher resolution can produce images with more pixels, which means better image quality. Higher resolutions will increase the accuracy of measurements made by the system.

3.2.2.4 Vision processing

The steps performed by the vision processing system during an inspection, Figure 27, are as follows:

1. Acquiring the digital image from the sensor.
2. Pre-processing the image to optimize it for measurements.
3. Analyzing the image to locate the features of the part inspected.
4. Collecting measurements of the features and comparing them with the defined criteria for that feature.
5. Establishing a result, such as, pass-fail, accepted-rejected or go/no-go condition.

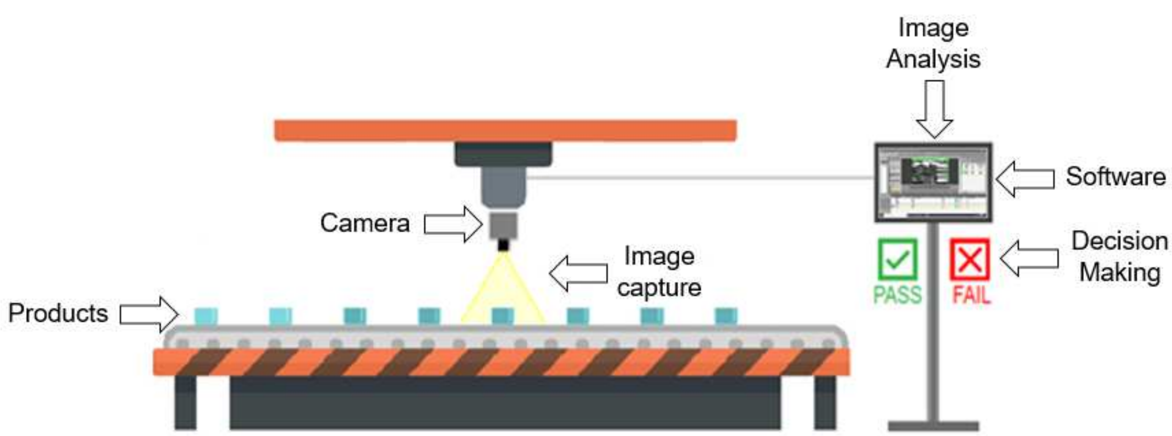

Figure 27. Inspection of the product process.

3.2.2.5 Communications

The last element in the vision system involves the communications protocol. This element provides a usable output in a standardized format that can provide a usable signal to drive other components in the production process based upon the output from the vision processing system. Standardized outputs include discrete I/O signals or serial data (RS-232, Ethernet) sent to a logging device that will make use of the data. A discrete I/O signal may be fed to a PLC. A serial RS-232 data feed can be fed to an HMI screen to display information of the production process to an operator.

The vision system process is described in the flow chart, Figure 28. When each product passes through an inspection sensor, which triggers a vision system to capture an image of the product. After acquiring the image and storing it in memory, vision software processes or analyzes it and issues a pass-fail response based on the range limits set in the program created. If the system detects a defective product- a fail-it signals a diverter to reject the product.

Data is collected to elaborate moving average control chart. The control chart will help to predict when is the appropriate time for tool replacement and also to have a record of the performance of the process before and after the replacement.

3.2.1 Design of products

To be able to do the inspection, several products were designed in *SolidWorks* (Figures 29, 30 and 31) and then created by a 3D printer at Morehead State University, (Figures 32, 33 and 34). The dimension of each block is 3.5x2.5x0.5in (88.9x63.5x12.7mm). Each product has three different shapes, a circle, a triangle, and a rectangle. In some blocks, a certain shape is missing to simulate a defective product to be able to see the program outcome in this situation. The real measures for each product pattern are the following: circle diameter is set as 1in (25.4mm), angle of a triangle is 63.5°, and the length of the rectangle is 1.5in (38.1mm). After the design is ready, the model needs to be saved as a file type STL to be able to open it in the 3D printer software.

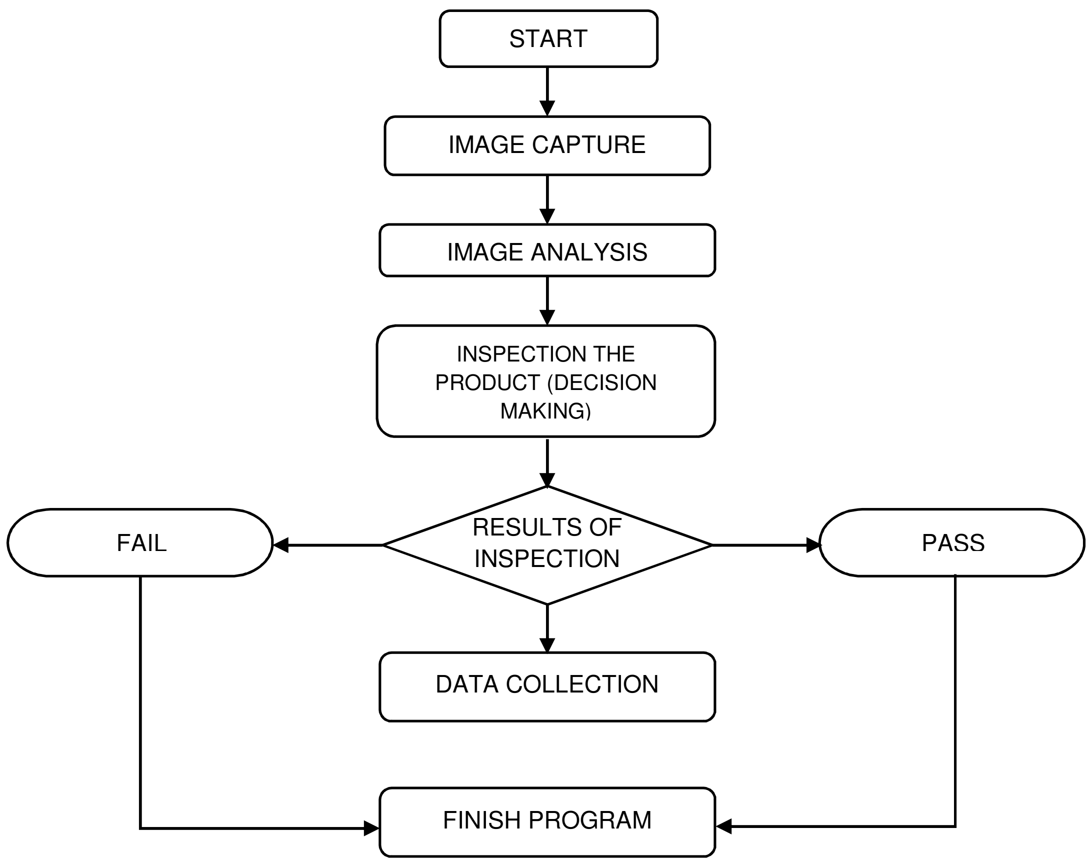

Figure 28. Flow chart of machine vision inspection.

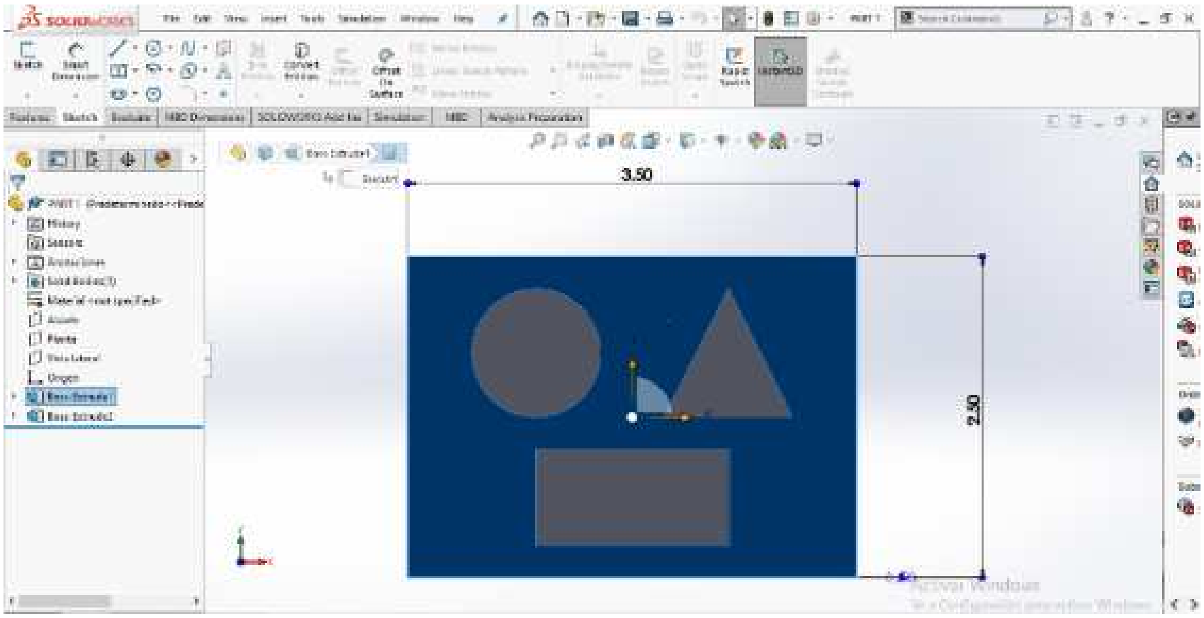

Figure 29. Design of product “a” in SolidWorks.

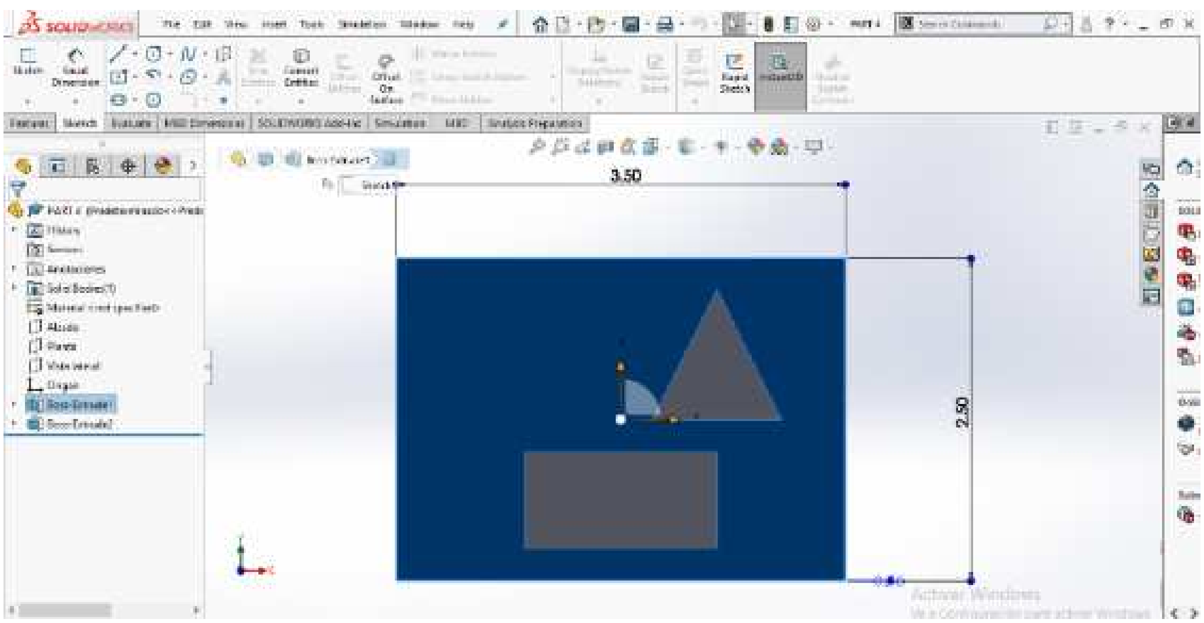

Figure 30. Design of product “b” in SolidWorks.

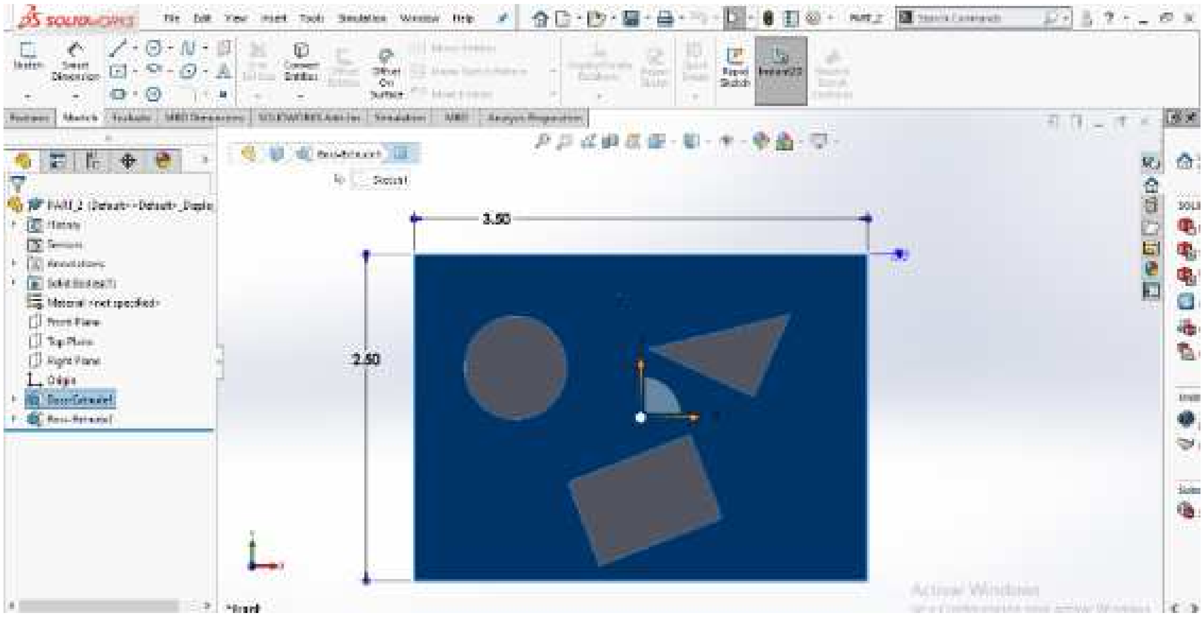

Figure 31. Design of product “c” in SolidWorks.

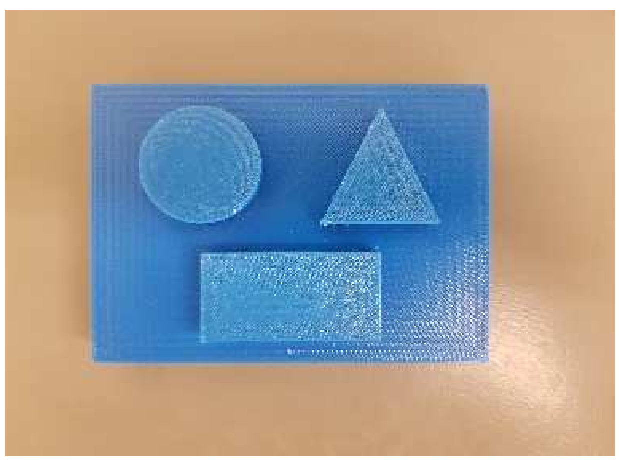

Figure 32. Product “a” printed in a 3D printer.

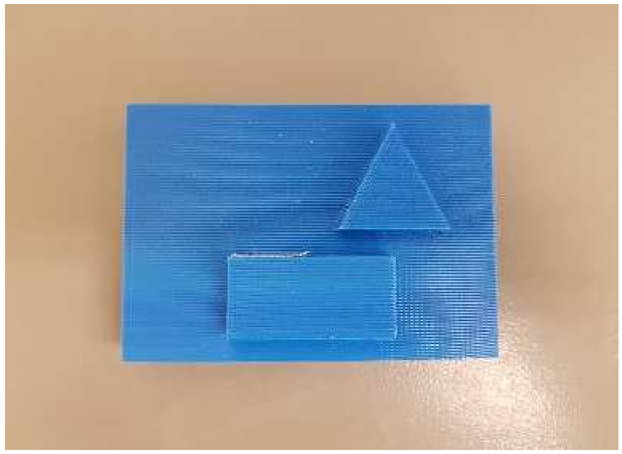

Figure 33. Product “b” printed in a 3D printer.

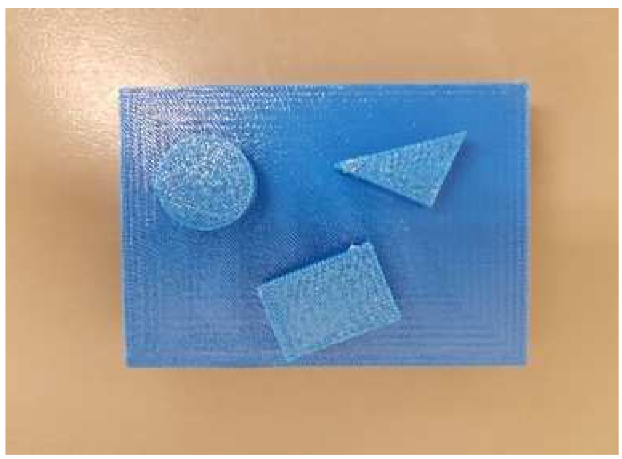

Figure 34. Product “c” printed in a 3D printer.

3.2.2 Development of a program for the inspection

The *In-Sight Explorer* software was used to develop the program to do the inspection of the products. The training inspection can be used with the emulator option to work remotely, without having the camera connected in real-time. Several images of products are captured with the vision system for later inspection with the program. The routine of the program consists in measuring the patterns (diameter of circle, angle of a triangle and length of a rectangle). For each pattern, the range limits will be adjusted based on customer requirements. If any of the products do not fall in the range limits set up, the product will be considered defective. The results of each inspection are collected to elaborate a moving average control chart in an excel file.

3.2.2.1 Set up image

The images of the products are uploaded to start a new program for inspection. The program requires results in real-world units. Therefore, the image's pixel coordinates are calibrated as 63.5mm (width 2.5in). The calibration type selected is the *Edge to Edge* option. The units selected are in millimeters. The dimension is specified, and the width from edge to edge is selected (Figure 35). Finally, the *Calibrate* option is selected to finish the set-up of the image.

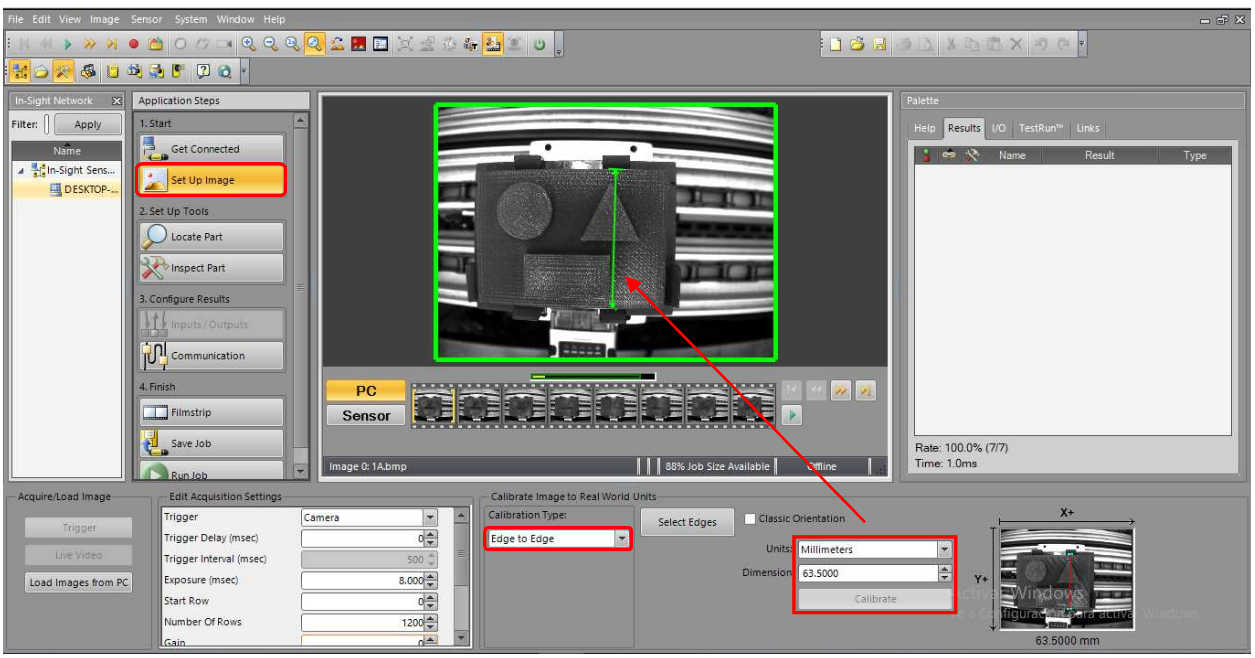

Figure 35. Set up an image in In-Sight Explorer.

3.2.2.2 Locate part

This step is used to define a feature in the image that provides positional data. A fixture is created to locate a part in the image, even if the part being inspected rotates. The *PatMax Pattern* tool is selected. The *Search* region is selected to cover the areas in the image where the *Model* pattern may appear (Figure 36).

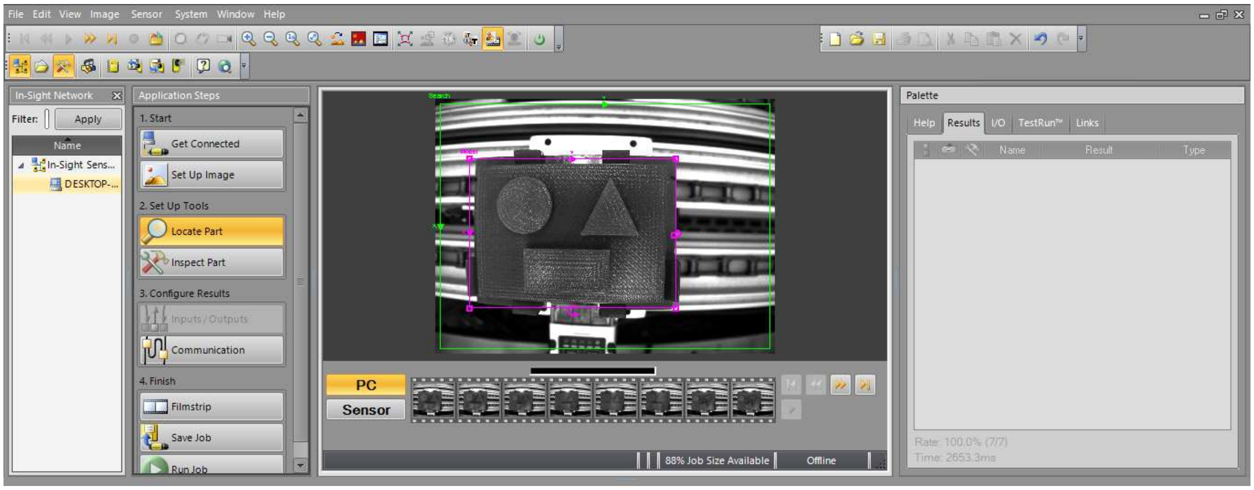

Figure 36. Search and model selection.

3.2.2.3 Inspect part

The tools that will be used to build the program are configured. The *Measurement tools* is selected and the *Circle Diameter* is added. The area where a circle is located and selected. The area to inspect the diameter of the block is shown after selecting the circle (Figure 37).

The diameter is shown in millimeters in the results palette as 25.345 (Figure 37). That measure is going to be used as the pattern reference for the incoming inspections. By selecting the *Diameter* tool in the results area, the *Edit Tool* is displayed. The *Range Limits* of the diameter can be adjusted for a more precise inspection (Figure 38). The *Range Limits* are given by default as the maximum of 27.88mm and a minimum of 23.811mm.

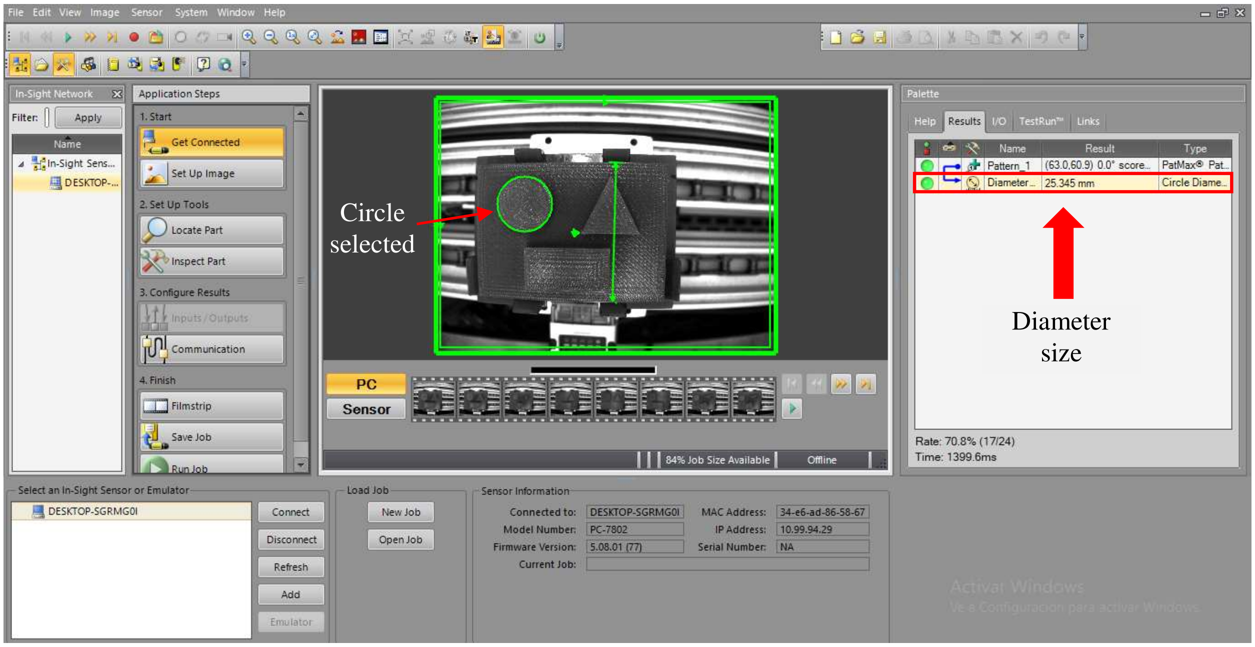

Figure 37. Diameter tool in results window.

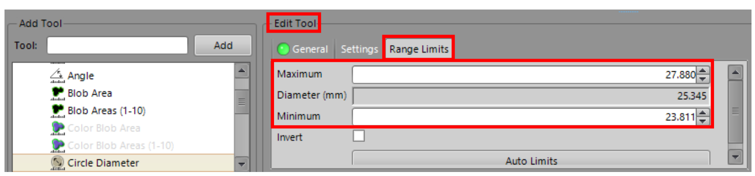

Figure 38. Adjustment of range limits.

The *Measurement tools* is selected again, and the *Angle* tool is added. With the *Angle* tool, the angle between two linear edges (Edge 1 and Edge 2) features is measured. The angle is shown in degrees in the results palette as 63.425 (Figure 39). If the angle is within the specified limits the product will be accepted. The product will be rejected if the measured angle is outside of the limits or the feature is not found. The *Range Limits* of the angle can be adjusted for a more precise inspection (Figure 39). The *Range Limits* are given by default as a maximum of 69.767 degrees and a minimum of 57.082 degrees.

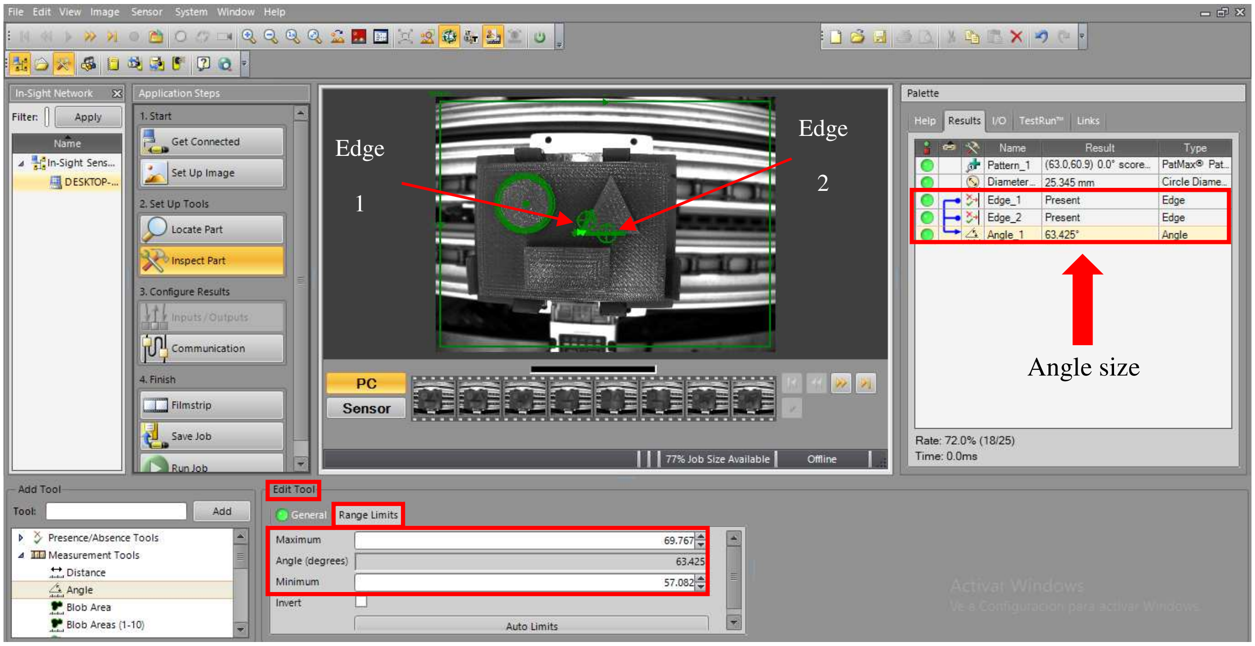

Figure 39. Angle tool and adjustment of range limits.

The final tool that is going to be used is the *Edge tool,* located under the *Presence/Absence Tools* menu. With the *Edge* tool, it can be determined whether or not linear edges are present or absent. If the edge is within the specified limits, the product will be accepted. The product will be rejected if the measured edge is outside of the limits or the feature is not found. Once the edge has been selected, it shows that the edge is present in the product block (Figure 40).

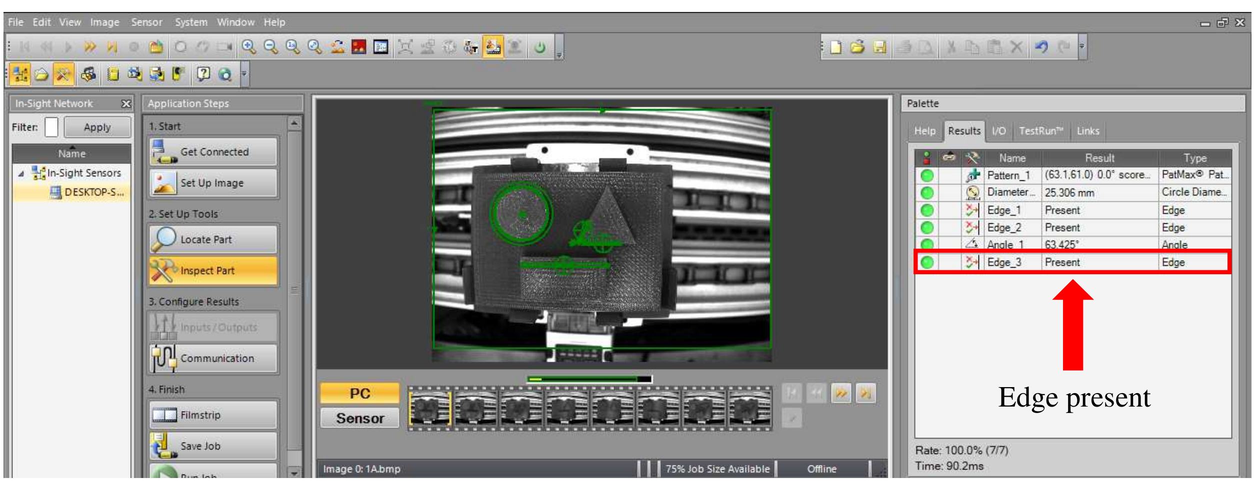

Figure 40. Edge selected.

3.2.3 Running the program for the inspection

Once the standard values are assigned for the accepted product, the program is ready to run for a test and determine whether the incoming products meet the standard tolerances or not. If the product does not meet the standard tolerances, it will be considered a defective one. The images are uploaded to the program to be able to do the inspection. The inspection will take place off-line.

The *Run Job* option is selected to start analyzing the product image. The reference product image is analyzed (Figure 41) and shows all the dimensions of the patterns (diameter, angle, edge) in the results palette. The color green indicates that the product has met the standard tolerances, which means the product has no defects.

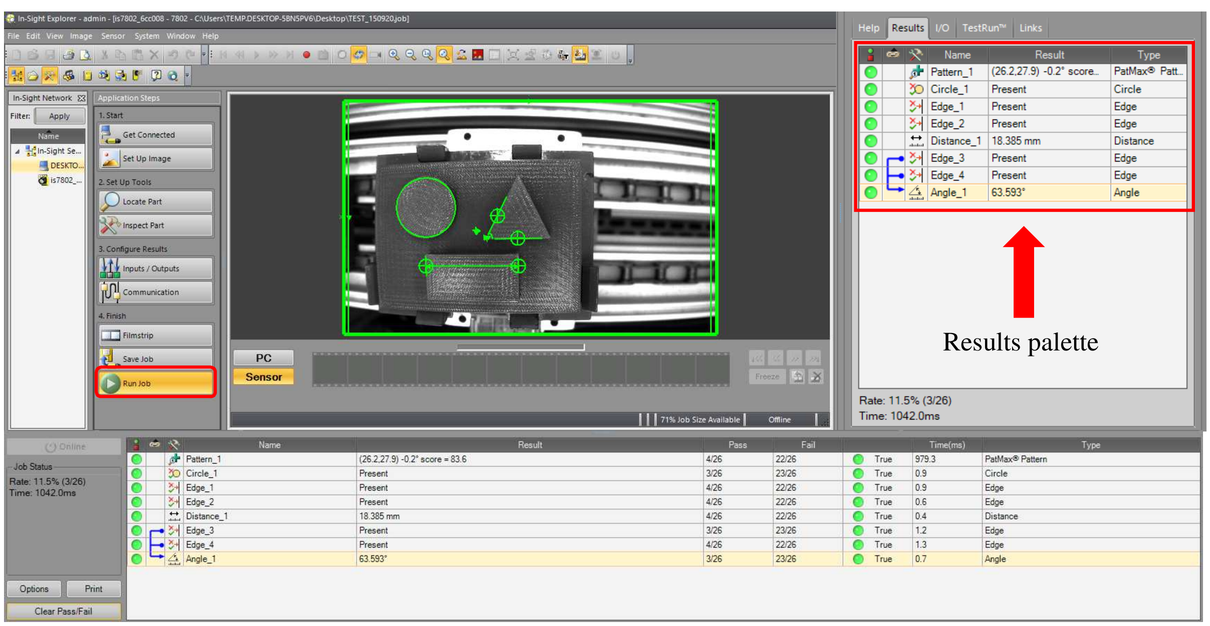

Figure 41. Inspection of a product.

3.2.3.1 Inspection of a defective product

When the program runs the job, the images captured of a “defective” product display and analyzed one by one and finally compared with the reference product. If one of the products is out of the standard tolerances, it will be indicated in the results palette. The program also detects when a pattern is not present in the product and displays in color red the missing part or area (Figures 42, 43 and 44). The patterns displayed in color green means that the standard values are satisfactorily met or are within the range limits set.

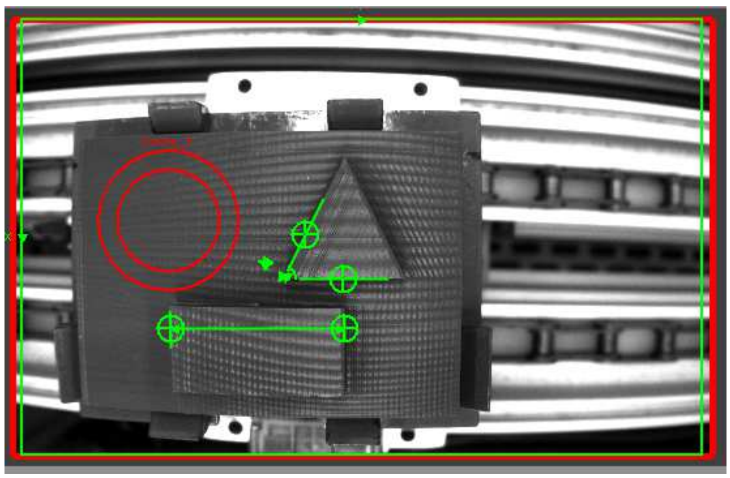

Figure 42. Inspection of a defective product.

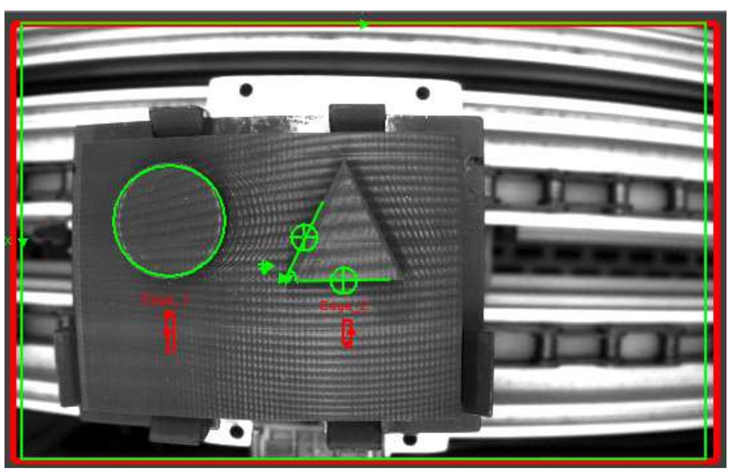

Figure 43. Inspection of a defective product.

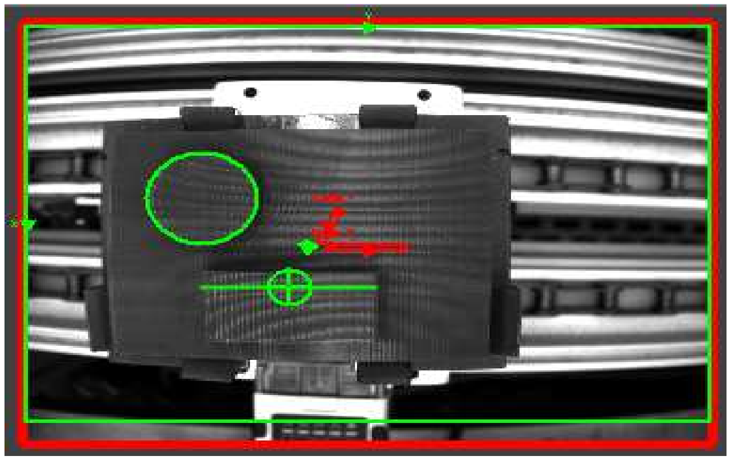

Figure 44. Inspection of a defective product.

In some cases, the product will have all the patterns but with different dimensions or locations. The program will do the inspection and indicate whether the product is within the standard values or not. Even though the pattern of the triangle is present on the product (Figure 45), it does not meet the standard values because it is out of the range limits. Therefore, the product will be considered defective.

In Figure 46, the circle is considered within the range limits, even though it is in a different location compared to the reference product. However, the triangle and rectangle patterns are in a different location than the ones in the reference product. Therefore, the program indicates in red where the parts are missing.

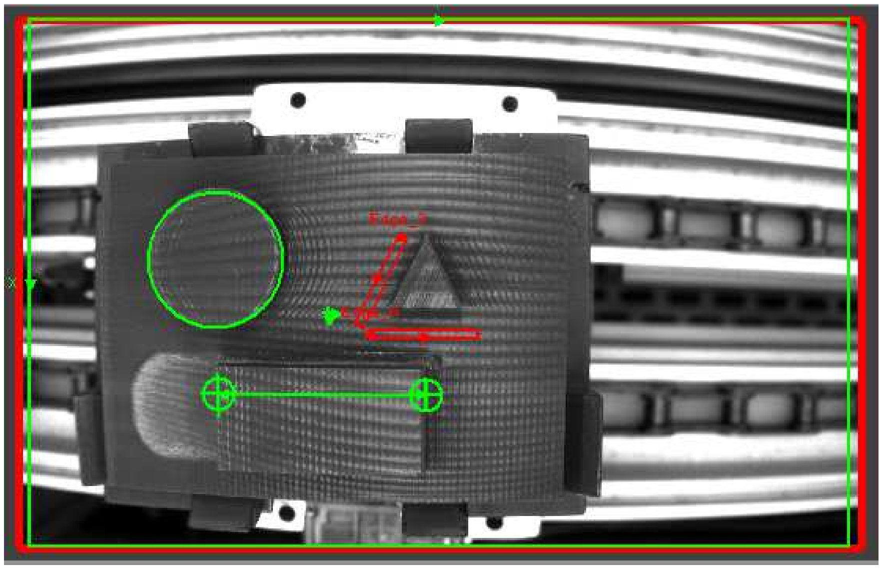

Figure 45. Pattern with a different dimension.

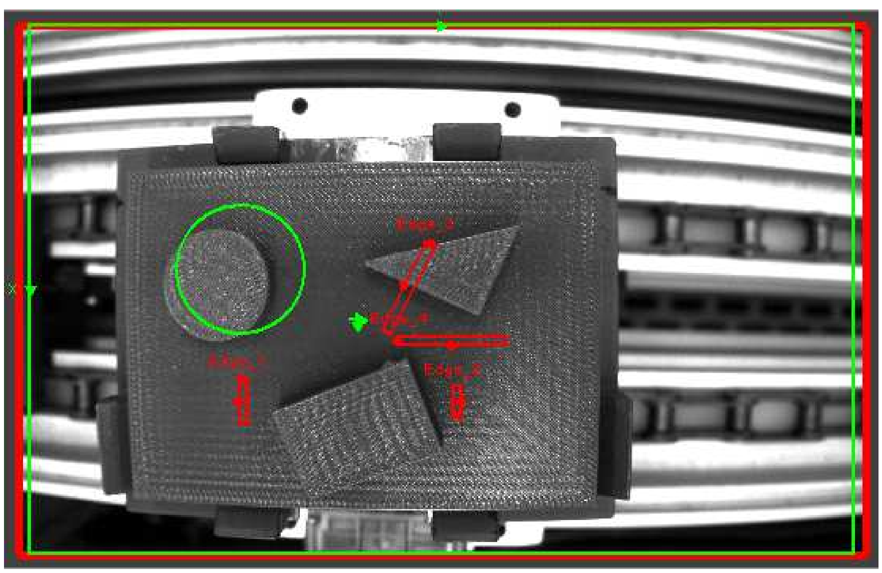

Figure 46. Pattern with a different location.

3.3 Data collection

During the inspection of each product, data from the measure of the diameter and angle is collected from the results palette to elaborate a table in an excel file. Finally, a moving average control chart is elaborated to evaluate the performance of the process, Figure 47.

Results from inspection

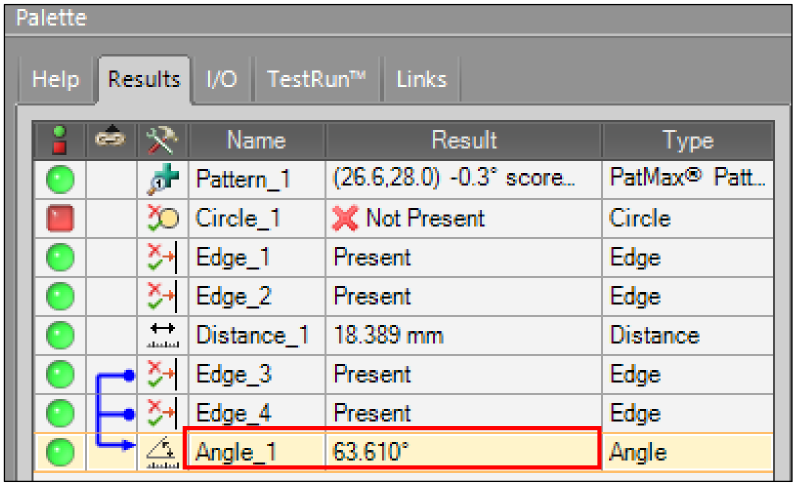

Table with data collected

Sample, *i*	*Xi*	*Mi*	*UCL*	*LCL*	*CL*
1	63.425	63.425	66.43	60.43	63.425
2	63.425	63.425	65.55	61.30	63.425
3	63.425	63.425	65.16	61.69	63.425
4	63.425	63.425	64.93	61.93	63.425
5	63.425	63.425	64.77	62.08	63.425
6	63.425	63.425	64.77	62.08	63.425
7	63.225	63.385	64.77	62.08	63.425
8	63.425	63.385	64.77	62.08	63.425
9	63.225	63.345	64.77	62.08	63.425
10	63.425	63.345	64.77	62.08	63.425
11	63.425	63.345	64.77	62.08	63.425
12	63.425	63.385	64.77	62.08	63.425
13	63.125	63.325	64.77	62.08	63.425
14	63.425	63.365	64.77	62.08	63.425
15	63.325	63.345	64.77	62.08	63.425
16	62.225	63.105	64.77	62.08	63.425
17	60.425	62.505	64.77	62.08	63.425
18	58.125	61.505	64.77	62.08	63.425
19	57.325	60.285	64.77	62.08	63.425
20	56.225	58.865	64.77	62.08	63.425

Moving average chart of the process

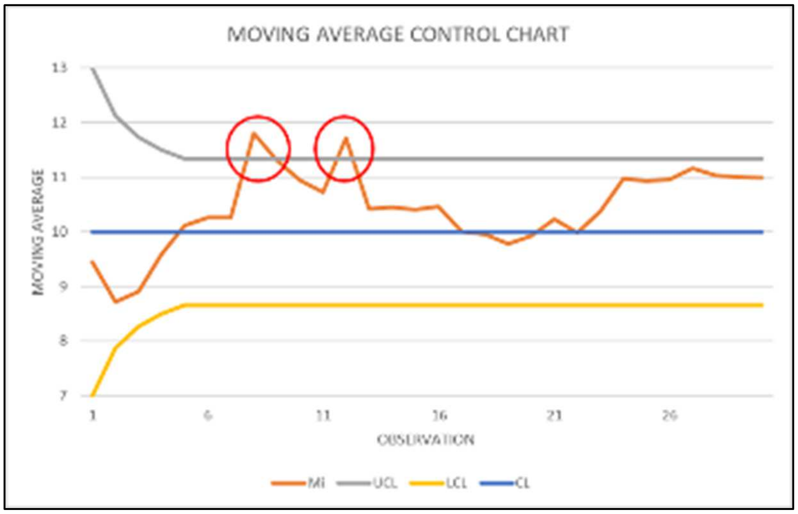

Figure 47. Data collection process.

3.3.1 Moving average control chart

The moving average control chart is a type of chart used to detect a change or shift in the process since it is more sensitive to shifts in the process than the traditional average and range control charts.

Individual observations are collected (x_1, x_2). The moving average of span *w* at the time *i* is defined as shown in equation 1:

$$M_i = \frac{x_i + x_{i-1} + \cdots + x_{i-w+1}}{w}$$

At period *i*, the oldest observation in the moving average set is dropped and the newest one is added to the set. The variance of the moving average M_i is as shown in equation 2:

$$V(M_i) = \frac{1}{w^2} \sum_{j=i-w+1}^{i} V(x_j) = \frac{1}{w^2} \sum_{j=i-w+1}^{i} \sigma^2 = \frac{\sigma^2}{w}$$

Therefore, if μ_0 denotes the target value of the mean used as the center line of the control chart, then the three-sigma control limits for M_i are as shown in equations 3 and 4:

$$UCL = \mu_0 + \frac{3\sigma}{\sqrt{w}}$$

$$LCL = \mu_0 - \frac{3\sigma}{\sqrt{w}}$$

The control procedure would consist of calculating the new moving average M_i as each observation x_i becomes available, plotting M_i on a control chart with upper and lower control limits given by equations 3 and 4, and it will conclude that the process is out of control if the M_i Value exceeds the control limits (*UCL, LCL*).

CHAPTER 4: FINDINGS AND RESULTS

4.1 Vision system

A vision system provides more consistent and reliable results from an inspection than the ones obtained by human inspection, Figure 48. With the program designed with the In-Sight Explorer software, the system can easily detect when certain patterns are missing or in a different location in a product. This facilitates the decision-making for quality control of the products.

Even though the emulator is a helpful tool to inspect the products off-line, several designs of the products are required to be elaborated (3D printer) to have different images (JPG) to simulate possible defects in the product. Also, it is necessary to have many samples for data collection, to elaborate the moving average control chart for better analysis of the process.

Figure 48. Vision system inspection process.

4.2 Data collection

The data collected from the measured angle and diameter during the inspection of the products are shown in Table 1 and Table 2, respectively, in millimeters. Twenty samples were taken to construct a moving average control chart. The data is a useful resource to detect any out-of-the-range limits in the manufactured product. It is important to keep a record of the data for comparison after tool replacement. In order to more accurately precede the right time for the replacement.

Table 1. Data from the measured angle.

Sample, *i*	*Xi*
1	63.425
2	63.425
3	63.425
4	63.425
5	63.425
6	63.425
7	63.225
8	63.425
9	63.225
10	63.425
11	63.425
12	63.425
13	63.125
14	63.425
15	63.325
16	62.225
17	60.425
18	58.125
19	57.325
20	56.225

Table 2. Data from the measured diameter.

Sample, *i*	*Xi*
1	25.345
2	25.345
3	25.145
4	25.345
5	25.345
6	25.045
7	25.345
8	25.345
9	25.445
10	24.345
11	24.245
12	24.045
13	24.245
14	24.345
15	24.345
16	24.145
17	23.945
18	23.645
19	23.345
20	23.345

4.3 Elaboration of moving average control chart

The chart will monitor the average angle of the triangle and the diameter of the circle pattern in every product. The measurements are taken from each product; the subgroup size is one. The measurements of the samples at a given time constitute a subgroup. The span (w) is the number of values to average at a time, and a span of 5 was chosen. The moving average of span w at the time i is defined as shown in equation 1. The control limits (UCL and LCL) are calculated using equation 3 and 4.

In equation 3 and 4, μ_0 is the target value of average or the overall average of the data that will be used for the center line, σ is the standard deviation of the moving average, and w is the span of the values.

4.3.1 Calculations for moving average control chart for angle inspection

The values used to calculate the control limits for the angle chart are as follow:

$$\mu_0 = 63.425,\ \sigma = 1,\ w = 5$$

The control limits for the angle chart are calculated with equation 3 and equation 4

$$UCL = \mu_0 + \frac{3_\sigma}{\sqrt{w}};\ = 63.425 + \frac{3(1)}{\sqrt{5}} = 64.77$$

$$LCL = \mu_0 - \frac{3_\sigma}{\sqrt{w}};\ = 63.5 - \frac{3(1)}{\sqrt{5}} = 62.08$$

The moving average for M_1 of span $w = 1$ is defined by equation 1.

$$M_1 = \frac{63.425}{1} = 63.425$$

The moving average for M_2 of span $w = 2$ is defined by equation 1.

$$M_2 = \frac{63.425 + 63.425}{2} = 63.425$$

The moving average for M_3 of span $w = 3$ is defined by equation 1.

$$M_3 \frac{63.425 + 63.424 + 63.425}{3} = 63.425$$

The moving average for M_4 of span $w = 4$ is defined by equation 1.

$$M_4 = \frac{63.425 + 63.424 + 63.425 + 63.425}{4} = 63.425$$

The moving average for M_5 of span $w = 5$ is defined by equation 1.

$$M_5 = \frac{63.425 + 63.424 + 63.425 + 63.425 + 63.425}{5} = 63.425$$

After sample M_5 ($M_6 – M_{20}$) the span will be considered $w = 5$. The moving average for M_6 of span $w = 5$ is defined by equation 1.

$$M_6 = \frac{63.424 + 63.425 + 63.425 + 63.425 + 63.425}{5} = 63.425$$

After calculating the moving average values ($M_1 – M_{20}$) the table is completed, as seen in Table 3. With the data obtained in that table, the moving average control chart is elaborated. The chart will be used to evaluate the performance of the process and thus be able to make a decision about the replacement of the tool on time.

Table 3. Angle samples.

Sample, *i*	*Xi*	*Mi*	*UCL*	*LCL*	*CL*
1	63.425	63.425	66.43	60.43	63.425
2	63.425	63.425	65.55	61.30	63.425
3	63.425	63.425	65.16	61.69	63.425
4	63.425	63.425	64.93	61.93	63.425
5	63.425	63.425	64.77	62.08	63.425
6	63.425	63.425	64.77	62.08	63.425
7	63.225	63.385	64.77	62.08	63.425
8	63.425	63.385	64.77	62.08	63.425
9	63.225	63.345	64.77	62.08	63.425
10	63.425	63.345	64.77	62.08	63.425
11	63.425	63.345	64.77	62.08	63.425
12	63.425	63.385	64.77	62.08	63.425
13	63.125	63.325	64.77	62.08	63.425
14	63.425	63.365	64.77	62.08	63.425
15	63.325	63.345	64.77	62.08	63.425
16	62.225	63.105	64.77	62.08	63.425
17	60.425	62.505	64.77	62.08	63.425
18	58.125	61.505	64.77	62.08	63.425
19	57.325	60.285	64.77	62.08	63.425
20	56.225	58.865	64.77	62.08	63.425

As shown in Table 3, samples 7, 9, 13, 15, 16, 17, 18 and 19 are not meeting the 63.425-degree standard value but they are still within the range limits (69.797-57.082). Sample 20 is the only one that is out of the range limits. A small variation in the samples started from sample 15 to sample 20. This may be a sign that the tool is starting to wear out and consequently, the products are beginning to show small defects.

The chart will help to confirm whether the machine requires tool replacement by analyzing the performance of the process.

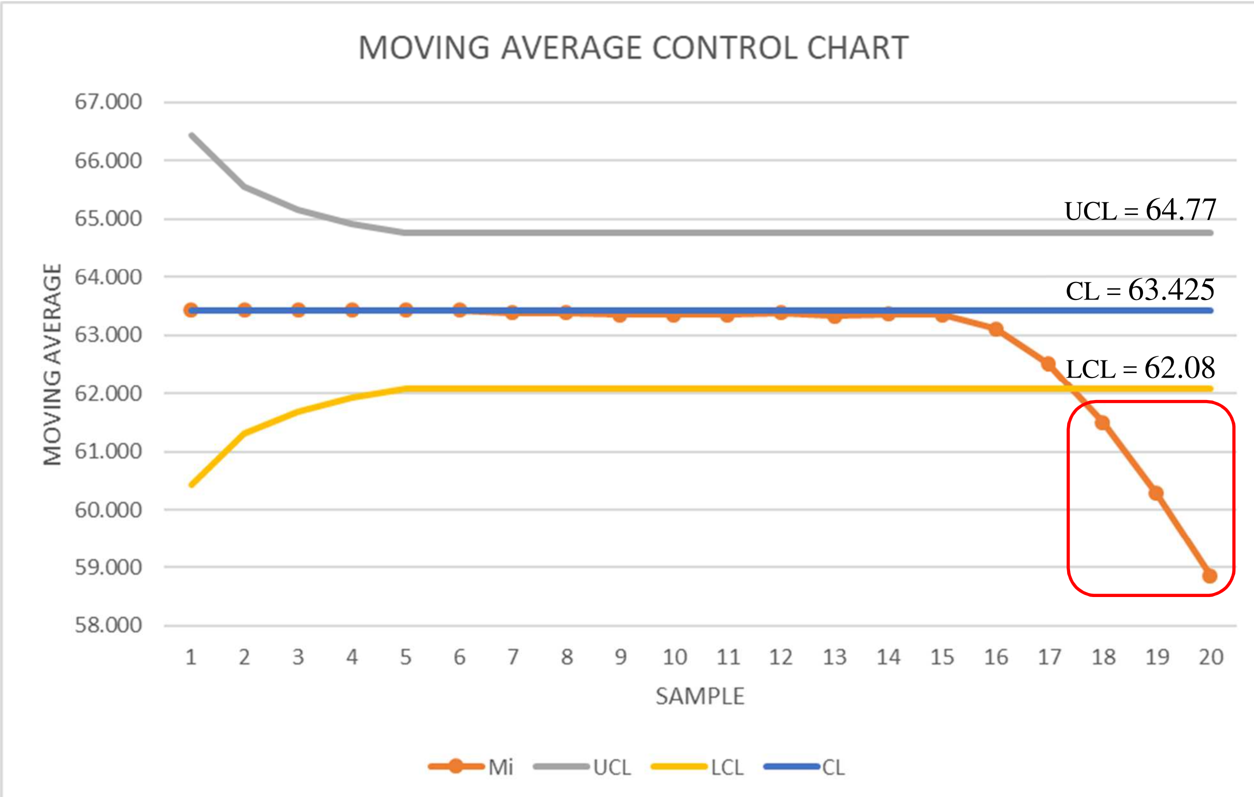

Figure 49. Moving average chart for angle inspection.

As seen in Figure 49, samples 18, 19, and 20 are under the lower control limit. Only sample 20 (X_{20} = 56.225) does not meet the minimum (57.082 degrees) range limit assigned by the inspection program.

By analyzing the moving average control chart shown in Figure 49, the trend indicates that the next samples will have defects, and they will not meet the established standards. One of the possible causes is that the tool is starting to present wear because of the variation in the measure of the products. This also means that a production shutdown has to be scheduled on time to make the tool change, in order to have waste of raw material and economic losses.

4.3.2 Calculations for tool wear control chart for angle inspection

A sample of five units of products is taken from the process. The results obtained are shown in Table 4. It is assumed that the specifications for the angle are at 63.43 and 63.45.

Table 4. Angle samples for tool wear chart.

Sample	*Xbar*	*R*
1	63.435	0.030
2	63.438	0.040
3	63.441	0.010
4	63.444	0.020
5	63.445	0.005
6	63.448	0.015
TOOL RESET		
7	63.436	0.005
8	63.437	0.015
9	63.44	0.005
10	63.442	0.030
11	63.445	0.005
12	63.446	0.020

It is important to visually examine data in order to understand the type of tool wear occurring. The tool wear chart, Figure 50, shows the trend of wear out of two series of data sets, in other words, before and after tool reset. It is critical to have a record of the trend before and after tool reset to determine as precisely as possible the life of the tool. The trend shows that the incoming products will be out of the specifications limits because the tool probably is starting to wear out. At that point, it is essential to schedule a production shutdown for tool replacement.

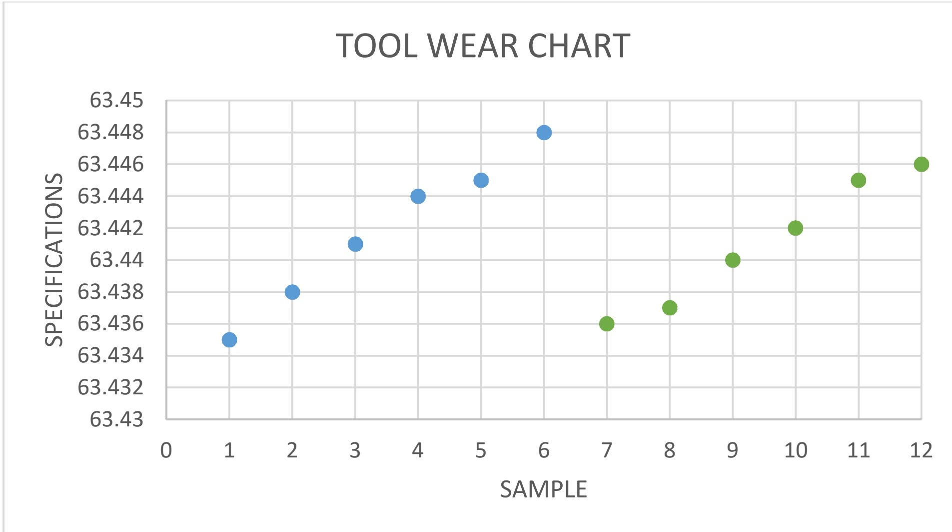

Figure 50. Tool wear chart for angle inspection.

4.3.3 Calculations for moving average control chart for diameter inspection

The values used to calculate the control limits for the diameter chart are as follow:

$$\mu_0 = 25.345,\ \sigma = 1,\ w = 5$$

The control limits for the diameter chart are calculated with equation 3 and equation 4

$$UCL = \mu_0 + \frac{3_\sigma}{\sqrt{w}};\ = 25.345 + \frac{3(1)}{\sqrt{5}} = 26.69$$

$$LCL = \mu_0 - \frac{3_\sigma}{\sqrt{w}};\ = 25.345 - \frac{3(1)}{\sqrt{5}} = 24.00$$

The moving average for M_1 of span $w = 1$ is defined by equation 1.

$$M_1 = \frac{25.345}{1} = 25.345$$

The moving average for M_2 of span $w = 2$ is defined by equation 1.

$$M_2 = \frac{25.345 + 25.345}{2} = 25.345$$

The moving average for M_3 of span $w = 3$ is defined by equation 1.

$$M_3 \frac{25.345 + 25.345 + 25.145}{3} = 25.278$$

The moving average for M_4 of span $w = 4$ is defined by equation 1.

$$M_4 = \frac{25.345 + 25.345 + 25.145 + 25.345}{4} = 25.295$$

The moving average for M_5 of span $w = 5$ is defined by equation 1.

$$M_5 = \frac{25.345 + 25.345 + 25.145 + 25.345 + 25.345}{5} = 25.305$$

After sample M_5 ($M_6 - M_{20}$) the span will be considered $w = 5$. The moving average for M_6 of span $w = 5$ is defined by equation 1.

$$M_6 = \frac{25.345 + 25.145 + 25.345 + 25.345 + 25.045}{5} = 25.245$$

With all the calculations performed as seen in Table 5, the table is completed with all the data necessary to elaborate the moving average control chart. The chart will be used to evaluate the performance of the process and thus be able to make a decision about the replacement of the tool on time.

Table 5. Diameter samples

Sample, *i*	*Xi*	*Mi*	*UCL*	*LCL*	*CL*
1	25.345	25.345	28.35	22.35	25.345
2	25.345	25.345	27.47	23.22	25.345
3	25.145	25.278	27.08	23.61	25.345
4	25.345	25.295	26.85	23.85	25.345
5	25.345	25.305	26.69	24.00	25.345
6	25.045	25.245	26.69	24.00	25.345
7	25.345	25.245	26.69	24.00	25.345
8	25.345	25.285	26.69	24.00	25.345
9	25.445	25.305	26.69	24.00	25.345
10	24.345	25.105	26.69	24.00	25.345
11	24.245	24.945	26.69	24.00	25.345
12	24.045	24.685	26.69	24.00	25.345
13	24.245	24.465	26.69	24.00	25.345
14	24.345	24.245	26.69	24.00	25.345
15	24.345	24.245	26.69	24.00	25.345
16	24.145	24.225	26.69	24.00	25.345
17	23.945	24.205	26.69	24.00	25.345
18	23.645	24.085	26.69	24.00	25.345
19	23.345	23.885	26.69	24.00	25.345
20	23.345	23.685	26.69	24.00	25.345

As shown in Table 5, samples 3, 6, 9, 10, 11, 12, 13, 14, 15, 16 and 17 are not meeting the 25.345 diameter standard values. Samples 18, 19 and 20 are out of the range limits (27.88-23.811). A small variation in the samples started from sample 10 to sample 20. This may be a sign that machine tool replacement is required soon. In order to avoid having defective machined products and waste of raw material.

The chart will help to confirm whether the machine requires tool replacement by analyzing the performance of the process.

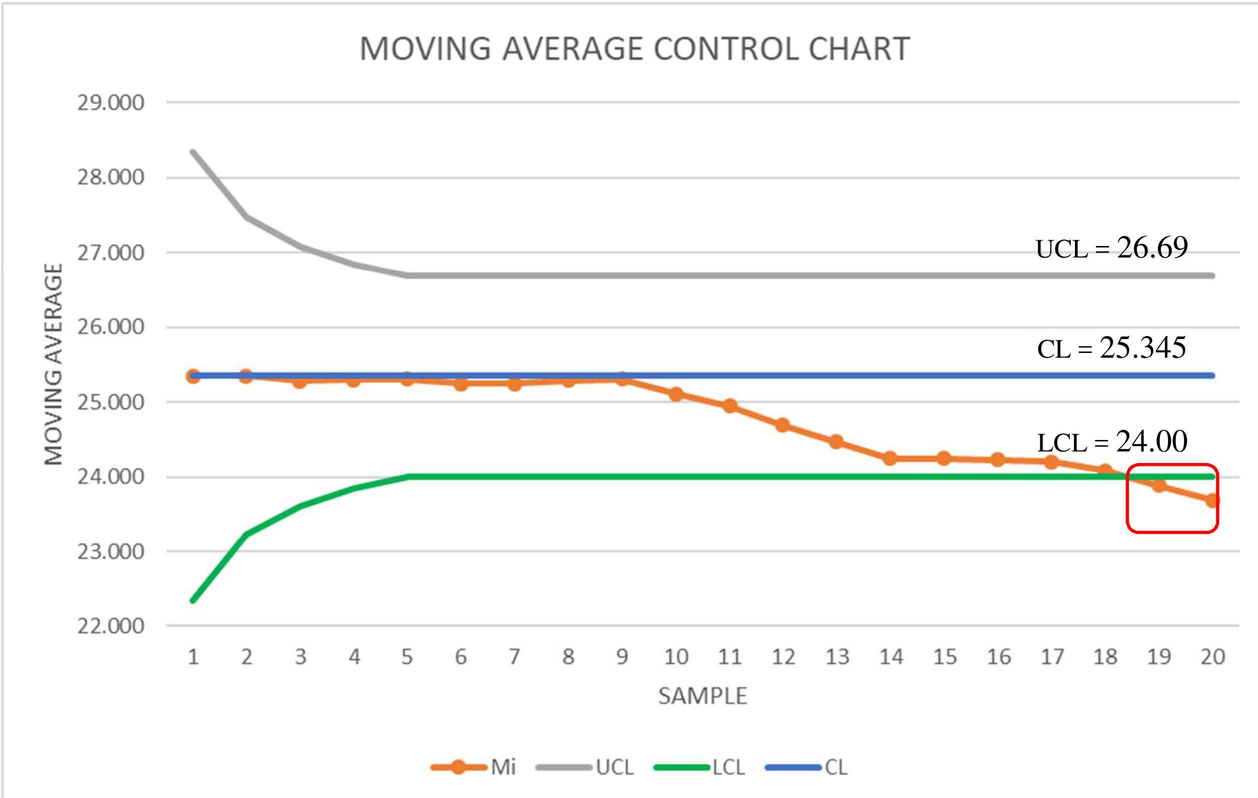

Figure 51. Moving average chart for diameter inspection.

As seen in Figure 51, samples 19 and 20 are under the lower control limit. Samples 18, 19, and 20 (X_{18} = 23.64, X_{19} = 23.345, X_{20} = 23.345) do not meet the minimum (23.811 millimeters) range limit assigned by the inspection program.

By analyzing the moving average control chart shown in Figure 51, the trend indicates that the products started to have variation since sample 10. The tendency shows that the next samples will have defects and will not meet the established standards. One of the possible causes is that the tool is starting to present wear because of the variation in the measure of the products.

CHAPTER 5: CONCLUSIONS

The objective of this research was to design a model that makes use of quality methods within a vision control system to inspect different features of test products, and based on the data obtained during the inspection, determine when is the appropriate time for tool replacement.

With the tools provided by the In-Sight software, a program can be developed to inspect different features or parameters (a diameter, an angle and a length) in every product. Several designs were elaborated in the 3D printer to carry out an inspection on-line.

One of the advantages of the software is the use of the emulator, it allows the user to work off-line without having the camera connected and work remotely. The disadvantage of the emulator is that it will require manual triggering. Different images need to be taken on-line and stored in the computer to later train with them.

Vision inspection can also be used in conjunction with statistical process control methods, like moving average control charts, to analyze trends in the measurements. By analyzing the charts (moving average, tool wear), it can be determined if the process is in or out of control. In this way, the necessary adjustments can be made to obtain the desired parameters and avoid the manufacture of defective products. It is important to keep records of the performance of the process before and after the tool replacement to be able to predict the appropriate time of the replacement.

Even though it is possible to determine when maintenance is required on a production machine with the use of a vision system, a proper maintenance schedule to the machine is required to avoid poor quality in the products, reducing scrap and unnecessary downtime.

Real time inspection in virtual reality would be a helpful tool in vision systems. By allowing the user to interact in a machine production process environment without having to elaborate real products to later train to do the inspection.

6. REFERENCE

Adeoti, O. A., & Olaomi, J. O. (2016). A moving average S control chart for monitoring process variability. *Quality Engineering, 28*(2), 212–219. https://doi.org/10.1080/08982112.2015.1104542

Al-Kindi, G., & Zughaer, H. (2012). An approach to improved CNC machining using vision-based system. *Materials and Manufacturing Processes, 27*(7), 765–774. https://doi.org/10.1080/10426914.2011.648249

Assembly. (2020, April 6). Boeing extends coronavirus shutdowns indefinitely. Retrieve from: https://www.assemblymag.com/articles/95632-boeing-extends-coronavirus-shutdowns-indefinitely, October 20, 2021

Byrne, G., & Sheahan, C. (2005). Comparative analysis of vision systems for electroplating surface quality inspection. *International Journal of Production Research*, 43(18), 3787-3801. doi:10.1080/00207540500103888

Chu, H., & Wang, Z. (2016). A vision-based system for post-welding quality measurement and defect detection. *The International Journal of Advanced Manufacturing Technology*, *86*(9-12), 3007-3014. doi:10.1007/s00170-015-8334-1

Cognex. (2021). Food and beverage. Retrieve from: https://www.cognex.com/es-mx/industries/food-and-beverage/packaging-inspection, November 4, 2021

Cognex. (2021). In-sight 7000 vision systems, Retrieve from: https://www.cognex.com/products/machine-vision/2d-machine-vision-systems/in-sight-7000-series, November 5, 2021

Du, X., Gai, J., & Chen, C. (2020). Condition-based maintenance optimization for motorized spindles integrating proportional hazard model with SPC charts. *Mathematical Problems in Engineering, 2020*, 1–11. https://doi.org/10.1155/2020/7618376

García-Ordás, M. T., Alegre, E., González-Castro, V., & Alaiz-Rodríguez, R. (2016). A computer vision approach to analyze and classify tool wear level in milling processes using shape descriptors and machine learning techniques. *The International Journal of Advanced Manufacturing Technology, 90*(5-8), 1947–1961. https://doi.org/10.1007/s00170-016-9541-0

Haggrén, H. (1987). Real-time photogrammetry as used for machine vision applications. *The Canadian Surveyor*, *41*(2), 201–208. https://doi.org/10.1139/tcs-1987-0015

Herakovic, N., Simic, M., Trdic, F., & Skvarc, J. (2010). A machine-vision system for automated quality control of welded rings. *Machine Vision and Applications*, *22*(6), 967–981. https://doi.org/10.1007/s00138-010-0293-9

Kerr, D., Pengilley, J., & Garwood, R. (2005). Assessment and visualisation of machine tool wear using Computer Vision. *The International Journal of Advanced Manufacturing Technology*, *28*(7-8), 781–791. https://doi.org/10.1007/s00170-004-2420-0

Klancnik, S., Ficko, M., Balic J., Pahole, I. (2015). Computer vision-based approach to end mill tool monitoring, *International Journal of Simulation Modelling, 14*(4), 571-583, doi: 10.2507/IJSIMM14(4)1.301.

Kuzmicki, D., & Sidorchik, D. (2017). Vision system for product quality control. *Mokslas – Lietuvos Ateitis / Science – Future of Lithuania*, *9*(3), 293-296 https://doi.org/10.3846/mla.2017.1040

Lee, KJ., Lee, TM. & Yang, MY. (2007). Tool wear monitoring system for CNC end milling using a hybrid approach to cutting force regulation. *Int J Adv Manuf Technol* *32***,** 8–17. https://doi.org/10.1007/s00170-005-0350-0

Martínez, S. S., Ortega, J. G., García, J. G., García, A. S., & Estévez, E. E. (2013). An industrial vision system for surface quality inspection of transparent parts. *The International Journal of Advanced Manufacturing Technology*, *68*(5-8), 1123–1136. https://doi.org/10.1007/s00170-013-4904-2

Martinova, L. I., Grigoryev, A. S., & Sokolov, S. V. (2012). Diagnostics and forecasting of cutting tool wear at CNC machines. *Automation and Remote Control*, *73*(4), 742–749. https://doi.org/10.1134/s0005117912040133

Montgomery, D. C. (2013). *Introduction to Statistical Quality Control.*

Ng, C. K., Wu, C. H., Ip, W. H., Chan, C. Y., & Ho, G. T. S. (2011). A real time quality monitoring system for the lighting industry: A practical and rapid approach using computer vision and image processing (cvip) tools. *International Journal of Engineering Business Management*, *3*, 22.

https://doi.org/10.5772/45670

Pham, D. T., & Oztemel, E. (1996). *Intelligent Quality Systems.*

Plex. (2021). Food and beverage manufacturers. Retrieve from Plex: https://www.plex.com/industries/food-and-beverage, October 26, 2021

QI Macros. (2021). Moving average control chart in excel. Retrieve from QI Macros: https://www.qimacros.com/control-chart/moving-average-chart/, October 26, 2021

Selvaraj, T., Balasubramani, C., Hari Vignesh, S., & Prabakaran, M.P. (2013). Tool wear by image processing. *International Journal of Engineering Research & Technology (IJERT). Vol. 2*. ISSN:2278-0181.

Sheu, S. H., & Lin, T. C. (2003). The generally weighted moving average control chart for detecting small shifts in the process mean. *Quality Engineering*, *16*(2), 209–231. https://doi.org/10.1081/qen-120024009

Sukparungsee, S., Areepong, Y., & Taboran, R. (2020). Exponentially weighted moving average—moving average charts for monitoring the process mean. *PLOS ONE*, *15*(2). https://doi.org/10.1371/journal.pone.0228208

Tangjitsitcharoen, S., Lohasiriwat, H. (2018). Intelligent monitoring and prediction of tool wear in CNC turning by utilizing wavelet transform. *Int J Adv Manuf Technol 99***,** 2219–2230. https://doi.org/10.1007/s00170-017-1424-5

Tangjitsitcharoen, S., & Boranintr, V. (2013). Integration of in-process monitoring and statistical process control of surface roughness on CNC turning process. *International Journal of Computer Integrated Manufacturing*, *26*(3), 227–236. https://doi.org/10.1080/0951192x.2012.731608

Thakre, A. A., Lad, A. V., & Mala, K. (2019). Measurements of tool wear parameters using machine vision system. *Modelling and Simulation in Engineering*, *2019*, 1–9. doi: 10.1155/2019/1876489

Trejo-Hernandez, M., Osornio-Rios, R. A., Romero-Troncoso, R. de, Rodriguez-Donate, C., Dominguez-Gonzalez, A., & Herrera-Ruiz, G. (2010). FPGA-based fused smart-sensor for tool-wear area quantitative estimation in CNC Machine Inserts. *Sensors*, *10*(4), 3373–3388. https://doi.org/10.3390/s100403373

Zaujec, Rudolf; Vopat, Tomas; Simna, Vladimir & Jurina, Frantisek (2018). Coating of cutting tool and cam milling strategy influence on the tool wear and surface roughness, *Proceedings of the 29th DAAAM International Symposium*, pp.1273-1278, B. Katalinic (Ed.), Published by DAAAM International, ISBN 978-3- 902734-20-4, ISSN 1726-9679, Vienna, Austria. doi: 10.2507/29th.daaam.proceedings.183

Zhou, Q., Chen, R., Huang, B., Liu, C., Yu, J., & Yu, X. (2019). An automatic surface defect inspection system for automobiles using machine vision methods. *Sensors*, *19*(3), 644. https://doi.org/10.3390/s19030644