A New Scheme for Monitoring and Diagnosis of Multistage Manufacturing Processes Using Product Quality Measurements

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ABSTRACT

The development of robust monitoring systems for assuring the consistency and stability of multistage manufacturing processes necessitates the use of add-on sensors and advanced data collection, storage, and analysis platforms to deal with the high-dimensional data collected from machines and products in multiple stages. In many cases, such an approach may not be feasible due to high implementation costs and the challenges of obtaining the process parameters and analyzing them effectively. This paper proposes an alternative approach for health monitoring and diagnosis of multistage manufacturing processes based on product quality measurements in a sensor-less environment. In the presented work, the available data consists of product quality parameters measured from multiple product types along with the manufacturing route associated with each product. A Gamma distribution is fit to the data for each parameter within a moving time window. Using the distribution fits, a metric is developed to represent the performance of each machine in a stage compared to its peers producing the same product. This metric is then aggregated across all the products produced by the machine to generate the final metric reflecting the overall performance of the machine. This performance metric is first calculated for the machines in the last stage. After flagging the underperforming machines in the last stage, the samples from those machines are removed from the data set and the remaining samples are used to calculate the similar metric for the prior stage. The suggested approach assumes the random distribution of products from one stage to the next to facilitate the implementation of a comparison-based approach. This approach is tested on a data set collected from a manufacturing plant. The results demonstrate the effectiveness of such approach for monitoring and diagnosis of multistage manufacturing processes when the data is not available from within the process.

1. INTRODUCTION

With the rapid advancement of science and technology, the manufacturing processes are becoming more and more complicated and so sustaining their performance and reliability becomes increasingly important and a pivotal factor in global market competition. This trend is driving the manufacturers to deploy more advanced and reliable process monitoring systems to improve the quality, productivity, and reliability of their processes. With the fast development of information and sensing technologies, large amounts of data are being collected from industrial processes. The availability of various resources for collecting data has led to the advancement of data-driven process control and monitoring technologies which has had a growing impact on the final quality of the products (Shu & Tsung, 2000). A large amount of research has so far been dedicated to the development of multistage process monitoring and diagnosis methods based on measurements in different stages of the processes (Asadzadeh & Aghaie, 2012; Shu & Tsung, 2000; Tsung, Li, & Jin, 2006; Wolbrecht, D'ambrosio, Paasch, & Kirby, 2000; Zhou, Huang, & Shi, 2003; Zhou, Ding, Chen, & Shi, 2003). The developed methods in this field can be categorized in two types: 1) methods based on variation propagation modeling techniques (Ceglarek, Shi, & Wu, 1994; Ceglarek & Shi, 1996; Hu & Wu, 1992; Liu & Hu, 1997); and 2) methods based on Statistical Process Control (SPC) techniques (Lucas & Saccucci, 1990; Montgomery, 2007; Neubauer, 1997; Page, 1954; Rato & Reis, ; Reynolds, Amin, Arnold, & Nachlas, 1988; Reynolds, Amin, & Arnold, 1990; Roberts, 1959).

One of the well-established variation propagation-based modeling techniques is Stream of Variation (SoV), introduced by J. Hu in (7) to identify the sources of variation in automobile body assembly. By developing the

inherent relationships between errors from various sources in a sheet metal assembly process, further improvements in SoV-based methods helped to solve two fundamental issues: 1) lack of analytical models for variation propagation, and 2) lack of a systematic methodology for analysis of variation propagation and its minimization (Shi, 2010). Despite the effectiveness of this group of approaches in modeling and diagnosis of multistage manufacturing processes, they require product quality measurements from each stage of the process in order to build the variation propagation model of the process.

The second group of methods mentioned previously in this section is based on SPC techniques. The objective of SPC is to monitor the process over time and determine whether the process is in control or not. SPC charts were first developed to monitor the key product variables in a univariate way (Lucas & Saccucci, 1990). The most commonly used traditional SPC charts include Shewhart, Cumulative Sum (CUSUM), and Exponentially Weighted Moving Average (EWMA) control charts (Reynolds, Amin, Arnold & Nachlas, 1988). In this group of methods, process data samples from either fixed or variable time intervals are taken. Depending on the selected method, a statistic is computed and plotted from the samples in each interval and thresholds are set to define the acceptable range of the variable. Similar to the SoV-based methods, SPC-based methods also require measurements in different stages of the process. If only the final product quality measurements are available, SPC can still be used to detect variations in the process. However, it is unable to provide further information regarding the source of the variation in terms of process stage and the machine or equipment causing the variation.

Despite the availability of process data in many manufacturing sites, there are existing challenges that the manufacturers face in measuring the necessary parameters from the processes. PHM implementation should have minimal adverse impacts on the performance of the monitored systems and at the same time, it should be low cost as well. Due to the complexity of industrial machinery and processes, instrumenting each machine with various sensors requires investment both in sensor and data acquisition hardware, and the infrastructure for data handling, storage and analysis. Besides considering the cost, the factors that should be considered for sensor selection include the parameters that need to be measured, performance needs, electrical and physical attributes of the system, and sensor reliability (Cheng, Azarian, & Pecht, 2010). Due to the existence of such barriers, data-driven manufacturing process monitoring often faces major challenges in dealing with limited resources and in many cases insufficient data to extract information from. As a summary, the common barriers for implementing sensor-rich manufacturing process monitoring systems are: 1) cost considerations including the initial and total lifecycle cost of sensors; 2) lack of access to critical locations; 3) sensor reliability; and 4) non-optimal selection of sensors and their location. Despite the significant impact of sensor technologies in recent advancements in PHM, there are still situations in which the implementation of sensors does not seem applicable due to the barriers mentioned above. Sensor cost is the most common issue that needs to be dealt with. Instrumenting numerous complex machines in a factory can impose a significant cost and in many cases is not deemed applicable. Such cost can both be related to the purchase of sensors and additional data acquisition and storage systems, or sensor and hardware maintenance and replacements. Determining and accessing the critical locations within the machines and processes is also a common challenge. An alternative sensor-less approach for manufacturing process monitoring is proposed in this paper. Although it may not be an option or the best option in many cases, it has proved to be a viable option in which sensory data from each machine is not available but the data regarding product quality and their manufacturing routes are available.

2. TECHNICAL APPROACH

2.1. General Concept

The process that this methodology is designed for may consist of several stages, with each stage having several machines. This process may produce multiple types of products. The data gathered from this process should include the quality measurements for each or sampled products, along with the manufacturing route associated with that product. Moreover, it is assumed that the products distribute randomly from machines in stage N to machines in stage N+1.

The data for this study includes a set of quality parameters measured for each product in a manufacturing plant. The data also contains the type of the product, its unique barcode, and its manufacturing route through the process. A gamma distribution is fit to the data for each parameter within a moving time window. Using the distribution fits, a metric is developed to represent the performance of each machine in a stage compared to its peers producing the same product. This metric is then aggregated across all the products produced by the machine to generate the final metric reflecting its overall performance. This performance metric is first calculated for the machines in the last stage. After flagging the underperforming machines in the last stage, the samples from under-performing machines in the last stage are removed from the data set and the remaining samples are used to calculate the similar metric for the prior stage. A flowchart of the proposed method is provided in Figure 1.

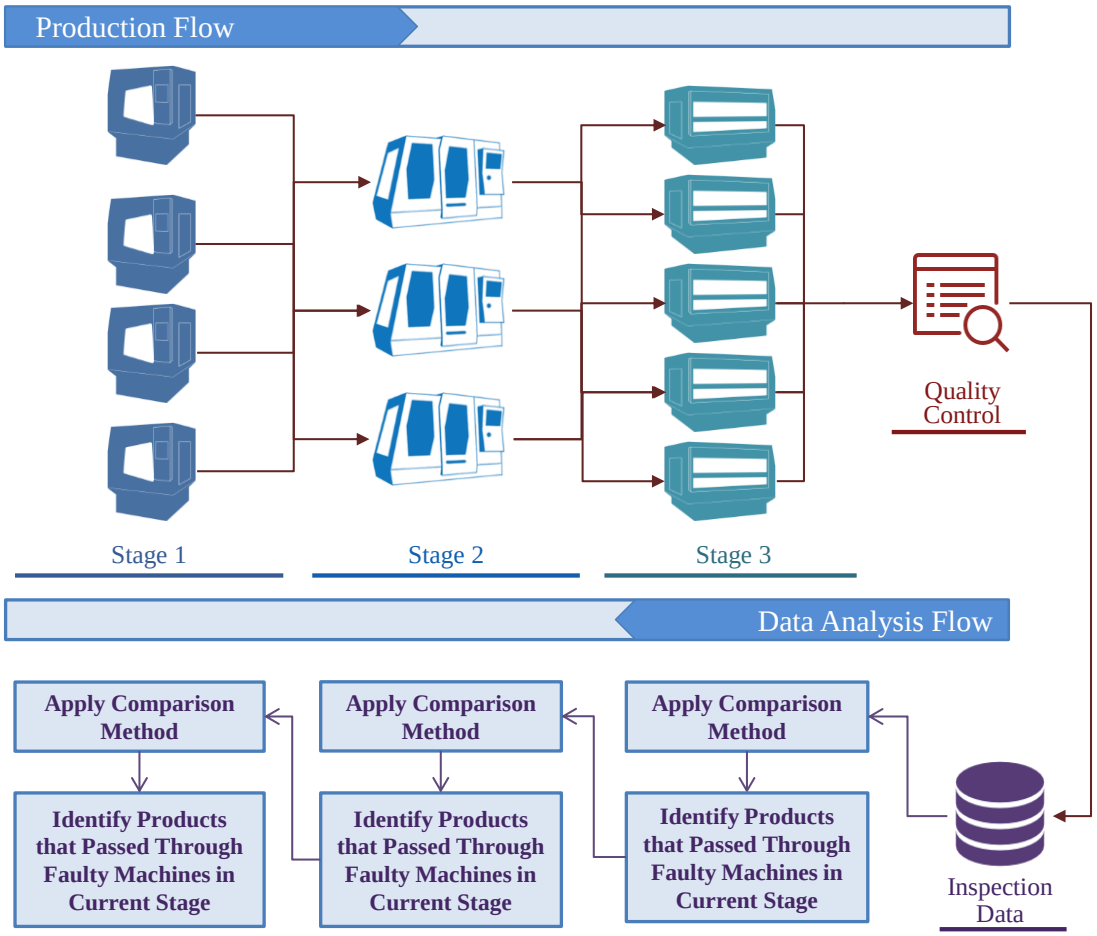

Figure 1. Flowchart of the proposed method for multistage manufacturing process monitoring and diagnosis.

2.2. Machine Performance Metric Development

For developing a comparison-based metric for machines, a window with the length of several hours was applied to the data. The length of the data was selected based on the expert knowledge and maintenance concerns. At each step of the window, the distribution of product quality parameters where considered as the source for calculating the metric. The purpose of developing such metric was to extract a standard health value, ranging from zero to one, which represents the performance of a machine relative to its peers. The first step for building such metric was to fit an appropriate distribution function to the data during each window.

As first step, the distribution of parameters for each product time and their possible shift over time was studied. The original values of the product quality parameters were positive real numbers, but due to proprietary concerns, the parameters were normalized between zero and one. The observed shape of the parameter distribution was close to normal (Gaussian), except when the parameter approached zero. This sharp drop-off in the distribution varied with the parameter, but it was never a hard cutoff at zero—it always sloped down to zero magnitude when the domain is zero. The negative slope (after the peak) had the appearance of an exponential distribution. Similar distribution shapes were observed for all the variables considered in this study. Thus, only one variable was picked and provided as an example. An example of the histogram of one of the parameters is shown in Figure 2. Initially, the option of exponential distribution was eliminated since the observed distributions had a peak at a finite positive value, whereas exponential distributions immediately decay from zero. The option of Gaussian distribution was also eliminated since its domain exists over the entire set of real numbers ($-\infty$, $+\infty$), and there was no negative-side "tail" on the distribution. Chi-squared distribution was considered, but it was ultimately eliminated for the more general gamma distribution, since the gamma distribution includes the scale parameter and thus was better able to fit the distribution of the parameter, whereas the chi-squared distribution "spreads out" as the shape parameter increases.

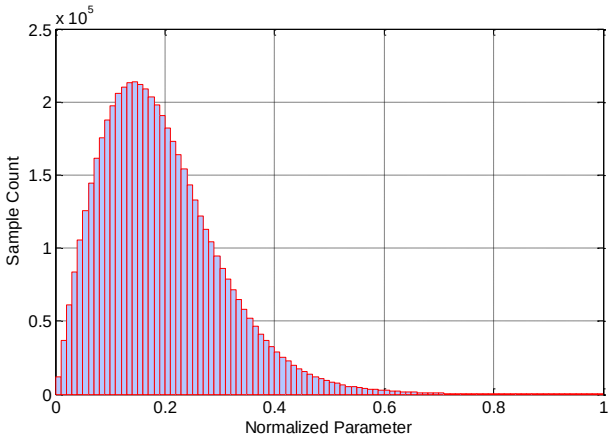

Figure 2. The histogram of a product quality parameter.

For a given set of a fairly large number of machines, where "large" is subject to discretion based on failure rate, it can be assumed that the majority of the machines will be functioning properly. The term "majority" indicates a number of machines among the total machines that is enough for creating a steady baseline performance. Thus, it is unlikely that a significant number of machines from this "large" set of machines will be faulty at any time, assuming repairs are regularly made on the faulty machines. For the purposes of this paper, "faulty" means any abnormal condition, whether it is a loss of calibration, a mechanical failure, a controller failure, or any other event which causes the machine's output to deviate from the correct output. Accordingly, an average of the parameters of all the machines should approximate a "good" condition. For the purposes of this paper, "good" means the state at or nearly at the point at which the machine yields the correct output. When comparing one machine against the average of all the other machines, a significant difference in distribution should indicate that the machine is in an abnormal condition.

When analyzing the data, it quickly became apparent that a method was needed for determining the difference in the distribution of a parameter for a machine versus the distribution of the same parameter for peers. Initially, the shared area under both probability density function (PDF) curves was considered as a percentage of the total area under the "good" average PDF curve. This value became the Confidence Value (CV) and was used as the health metric. Since the total area under a PDF curve is simply one, the CV could obtain a maximum value of one when the selected machine's parameter distribution function lay directly atop the averaged parameter distribution function. A minimum value of the infinitesimal approaching zero could be obtained when the means of the averaged and selected distributions are very far apart. Ergo, the CV was part of the set of (0, 1], where higher values indicated a more healthy condition and lower values indicated the reverse. The equation for calculating the CV is provided in Eq. (1):

$$\mathrm{CV} = \int_0^{+\infty} \min\left(\mathrm{PDF}_{\mathrm{selected}}, \mathrm{PDF}_{\mathrm{avg}}\right) dP \quad (1)$$

where *P* is the product quality parameter. The issue with this method was when the selected machine's parameter distribution had a tighter spread than the averaged machine. While the selected machine's data still fell within the accepted, averaged bounds, the area under both curves was minimal since a large portion of the area in the averaged parameter is in the positive and negative "tails" of the distribution.

The majority of the values of the given parameter will fall within one standard deviation bounds of the machine. To overcome the aforementioned issue, comparing the PDF's of the distributions only within one standard deviation bounds was considered. The equation was chosen to just be the area under the selected machine's PDF over the one standard deviation limits of the PDF of the averaged machines, as shown in Eq. (2):

$$\mathrm{CV} = \int_{\mu_{\mathrm{avg}}-\sigma_{\mathrm{avg}}}^{\mu_{\mathrm{avg}}+\sigma_{\mathrm{avg}}} \mathrm{PDF}_{\mathrm{selected}}\ dP \quad (2)$$

where *P* is the product quality parameter. Because either the positive or the negative "tails" of the selected machine's PDF will always pass through this domain, the lower limit of the function is some positive infinitesimal. The upper limit, where the area under the selected machine's PDF is almost wholly within the limits of the integral, is some infinitesimal less than one. Ergo, the CV is some positive real number on the set of (0, 1). This solved the problem of when the PDF of the parameter of the selected machine is much taller and narrower (sharper) than the PDF of the averaged function.

However, it added a new potential for error. When the PDF's were almost the same, the CV would approach 0.7 rather than one. This happened because roughly 70% of the area is within the one-sigma limits. To combat this error, the confidence value equation was changed such that the CV was equal to the percentage of the area under the one-sigma limits of the selected machine's PDF that intersected the one-sigma limits of the averaged PDF (Eq. (3)):

$$\mathrm{CV} = \frac{\int_{\max\left(\mu_{\mathrm{avg}}-\sigma_{\mathrm{avg}},\,\mu_{\mathrm{selected}}-\sigma_{\mathrm{selected}}\right)}^{\min\left(\mu_{\mathrm{avg}}+\sigma_{\mathrm{avg}},\,\mu_{\mathrm{selected}}+\sigma_{\mathrm{selected}}\right)} \mathrm{PDF}_{\mathrm{selected}}}{\int_{\mu_{\mathrm{selected}}-\sigma_{\mathrm{selected}}}^{\mu_{\mathrm{selected}}+\sigma_{\mathrm{selected}}} \mathrm{PDF}_{\mathrm{selected}}} dP \quad (3)$$

This confidence value is bounded on the range of (0, 1]. For healthy machines that fit the average healthy value, the CVs would be around 0.95 to 1. Faulty CVs are chosen based on a threshold CV that varies dependent upon the application of

this technique. Examples of three different cases with CV values ranging from near zero to one are shown in Figure 3.

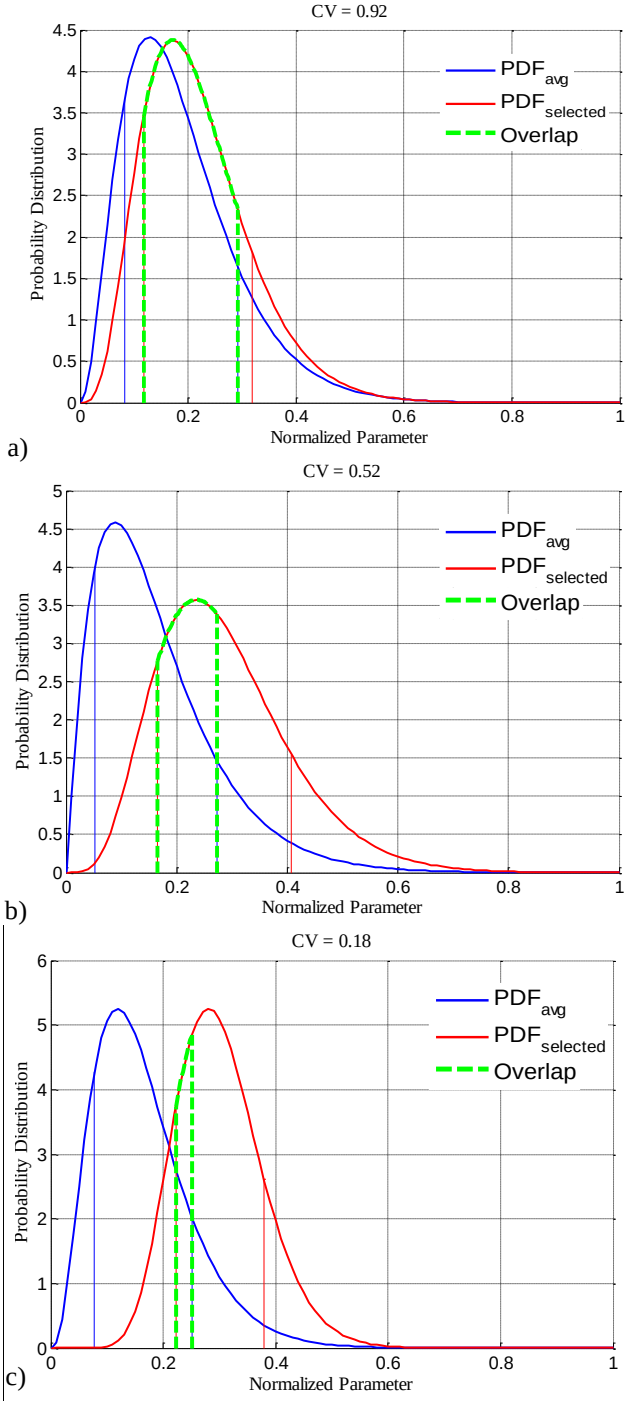

Figure 3. Examples of the metrics calculated within one time window: a) two very similar distributions yielding a CV of close to 1; b) two distributions yielding a CV of around 0.5; c) two significantly different distributions yielding a CV of close to 0.2.

While this technique worked, the performance cost of calculating and fitting the gamma distributions was higher than might be necessary. Additionally, having a software statistics package capable of fitting gamma distributions might not always be the case. Thus, as an alternative to gamma distribution, the authors further used normal distribution as an alternative with less computational requirements and slightly less accuracy. Accordingly, the gamma distributions were approximated as normal distributions. For any cases where the shape parameter of the gamma distribution (commonly represented by k) is large enough (normally 5 or higher), the normal distribution becomes a reasonable approximation of the gamma distribution for PDF values not near zero. Since the given technique uses at the farthest from the mean the one-sigma bounds which are still part of the "hump" of the PDF curve, this error does not normally come into play.

For rough estimations, a different equation for calculating the CV can be used. In this method, the standard deviation is ignored and only the mean values of the selected machine's parameter and the averaged machines' parameter are compared, as shown in Eq. (4):

$$CV = 1 - \left| 1 - \frac{\mu_{sel}}{\mu_{avg}} \right| \qquad (4)$$

Results seemed promising, as shown in Figure 4. The gamma distribution fit is plotted in blue, the normal distribution fit is plotted in red, and the mean comparison is plotted in green.

As can be seen in the Figure 4, the machine was run for a while, and then the CVs began dropping rapidly. Then production stopped for maintenance. When production was restarted following the maintenance, the CVs were back in the normal range. The normal approximation to the gamma distribution worked well, and the mean comparison worked as a rough estimate of the gamma distribution method.

2.3. Process Performance Monitoring

Besides calculating the health metric for each machine, the framework suggested in this paper also includes a methodology through which multiple stages of the process could be monitored and the machines adversely impacting the quality of the final products could be identified. The suggested approach for identifying faulty machines along the manufacturing rout is constructed based on a general assumption. It is assumed that products are being randomly distributed from each stage to the next. Having this assumption in place, the suggested approach analyzes the manufacturing process in reverse order. Therefore, the first step is to calculate health metrics for a specific type of product at the last stage of the production. After identifying the machines and the time frames in which the machine(s) affected the product quality, these samples are filtered out from the data and the remainder of the data is used to assess

the machines performance in the previous stage. Removing these samples help to filter out any effect by current stage machines on the product quality once moving back to the previous stage. Based on the random distribution assumption, this sample removal process will not mask any faulty situation coming from previous stages as the fault signature would be present in the products distributed amongst all the machines at the current stage. Once the metric based on the remainder of the data is calculated, the same procedure is performed for previous stages until it reaches the first stage. The suggested approach for an example of a three-stage manufacturing process is illustrated in Figure 5.

3. RESULTS AND DISCUSSION

In section 2.2, the general approach for calculating a comparison-based machine performance metric based on product quality parameters was discussed. Subsequently, in section 2.3, an approach for extending the machine performance metrics from covering one stage of the process to covering all the stages of the process was introduced. In this section, an example is provided from a small subset of data to demonstrate the performance of the suggested process monitoring approach. The selected subset includes data acquired from the manufacturing process during three days. Over ten quality parameters are measured from each product manufactured during the selected time period. Although for this particular data set all the products are undergone quality check but the suggested approach is applicable to the situations in which the quality check is being done by random sampling. . The data is limited to only one type of product at two stages of production. At stage one, there is only one machine, and in stage two, there are 12 machines. Having only one machine at first stage does not allow the implementation of a comparison-based approach. Hence, in this situation, the historical data that one machine is used to create a baseline. This baseline is later used to compare the current performance of the machine against it.

The data was analyzed by calculating comparison-based metric for each of the product quality parameters.. Using all the metrics calculated based on these parameters, one final metric needs to be extracted as the health indicator of the machines. Simply averaging all the calculated metrics may not be effective since there are cases in which among all the parameters, only one or two contain deviation from normal. In order to address this issue, during each time window, the minimum value among the metrics is considered as the final metric. Although more complex statistical features might convey additional information about the machine condition or severity of faults, but the minimum value represent robust performance in identifying faulty machines. This can be the direction of future works on this method to improve the suggested approach.

The purpose of this example is to show how the suggested method can determine the root cause of the problem and isolate it within a stage and a machine by taking into account the manufacturing route of each product. Figure 6 shows the machine health metrics for nine selected machines out of total of 12 machines in stage two. The other three machines are not included in the chart to avoid taking up more space as their data does not provide any additional information and is pretty similar to the presented ones. It can be observed that in machines 2, 6 and 9, there is a noticeable deviation from normal behavior. While the performance of the machines 2 and 9 declines in the short term, machine 6 underperforms consistently throughout the time window shown. These machines were detected as faulty as they were deemed to adversely affect the quality of the products. In the next step, the products gone through these machines were filtered out from the data and the remainder of the data was used for calculating the health metric for the machine in stage one. For filtering out the mentioned samples, a threshold was obtained by applying k-means clustering approach to the data, similar to how it is used in (Siegel & Lee, 2011). The purpose of using k-means was to partition all the calculated CV's into two clusters of normal and faulty. Figure 7 shows the clusters detected by the algorithm. Based on the results from k-means algorithm, the threshold of 0.65 was selected for determining the underperforming machines. After removing the samples affected by the faulty machines, the metric for the machine in stage one was calculated. For comparison, this metric was also calculated without removing the samples from machines in stage 2. Figure 8 shows both metrics for machine in stage one. The blue line shows the metric based on all the samples. After removing the samples affected by machine 9 in stage 2, a portion of the metric inclined significantly (red line in Figure 8). The overall increase in the metric within the shown time period is correlated to the removal of samples produced by machine 6 (Figure 6). Therefore it can be inferred that the remaining low CV values within the red line are due to faulty machine in stage 1. Special cases might happen when even until stage 1, some of low quality products are not being captured by the method. In those special cases it is possible that an environmental factor or raw material, which equally affects all the machines, are the root cause of low quality products.

4. CONCLUSION

This paper provides a machine health monitoring approach for manufacturing processes by relying only on the product quality measurements. Although the advancement and availability of sensing technologies provides a rich information source for PHM scientists and engineers to monitor the machines, the suggested method provides an affordable alternative approach for situations in which the implementation of the sensors are too costly or impractical.

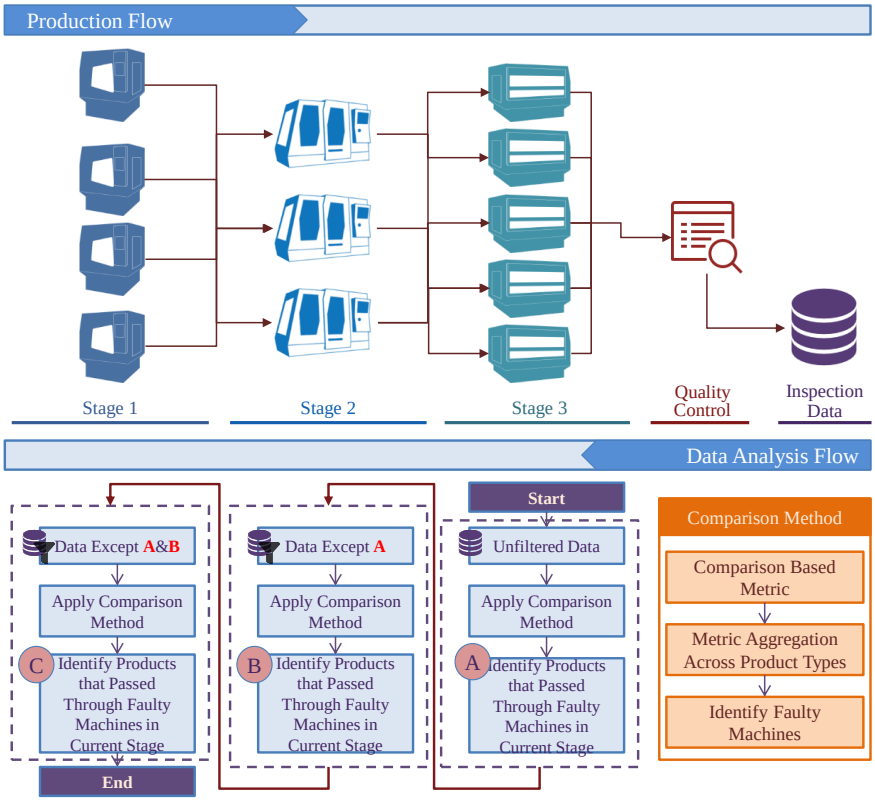

Figure 5. The flowchart of the proposed approach for an example of a three-stage manufacturing process.

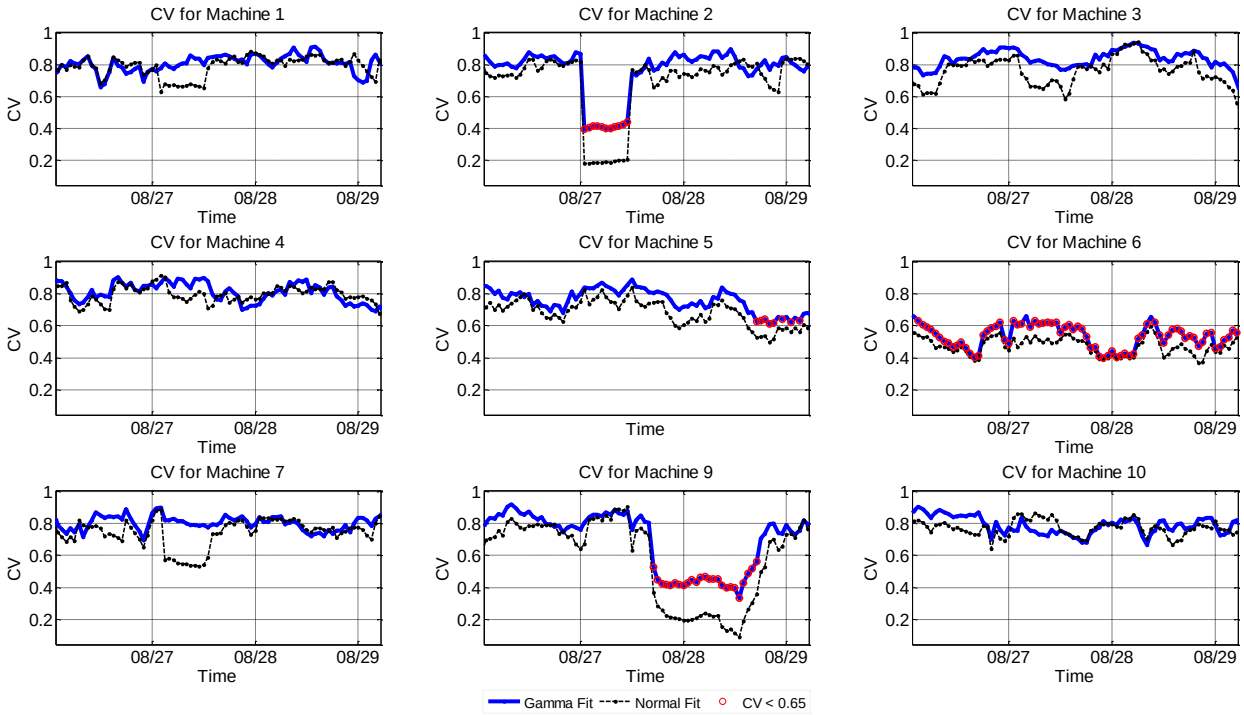

Figure 6. Calculated CV for four machines in stage 2 producing the same type of product.

The comparison-based method has been applied to a two staged manufacturing data where quality measurement values used as inputs of the suggested method. The method was able to identify underperforming machines in second and first stage of the manufacturing process by only relying on product quality measurements. There is potential to improve the suggested method by using other statistical features in calculating the final CV value (comparing to use minimum now).

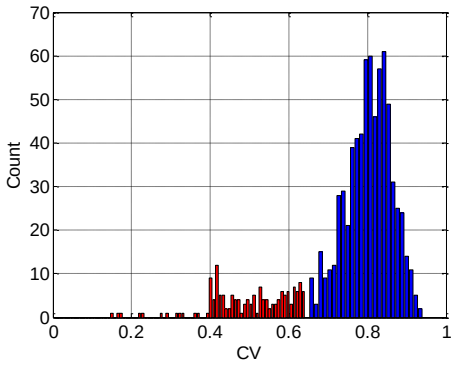

Figure 7. K-means clustering results using CV's calculated in stage 2. The two clustered identified by k-means are shown in blue (healthy) and red (faulty).

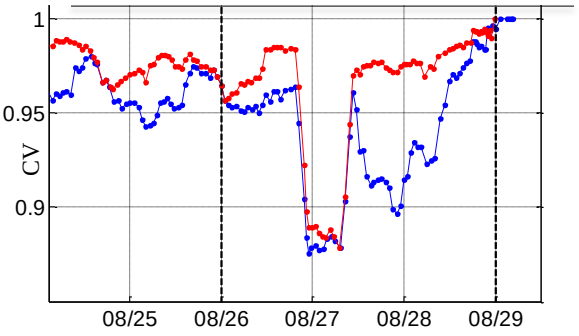

Figure 8. Calculated CV for the machine in stage 1 before removing the samples from stage 2 (blue) and after removing the samples from stage 2 (red).

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