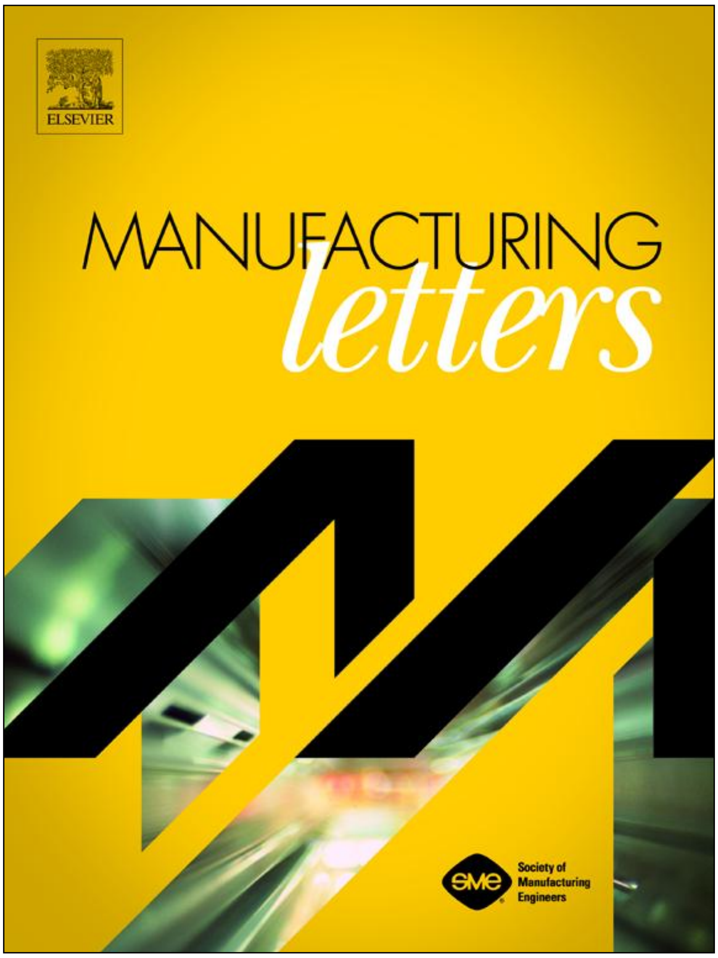

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Letters

Process-Monitoring-for-Quality—Applications

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ABSTRACT

Innovation and the marketplace have been pushing *Statistical Process Control (SPC)* outside its comfort zone, which requires a mature understanding of the product and process and a methodology for verifying the quality of each manufactured item. Especially when a new technology is proven to work and customer interest is high, companies want manufacturing to respond to the uncertainties. *Process Monitoring for Quality (PMQ)* is a strategy, based on the empirical learning and data gather capabilities of the Big Data environment, that addresses this challenge while verifiably producing quality product. *PMQ* offers opportunities for learning and quality improvement: it enhances the quality movement by addressing three quality problems that SPC or traditional quality control techniques cannot; and by illuminating future applications.

1. Introduction

Big data [1], Industrial Internet of Things [2], acsensorization [3], artificial intelligence [4], machine learning [5], and cyber-physical systems [6] are propelling smart manufacturing. Many technical and organizational challenges of smart manufacturing must be addressed in order to realize gains over the entire value network [1,7]. This letter identifies some challenges to traditional quality control that can now be addressed by *PMQ*, which was first introduced in [3].

PMQ is a big data-driven quality philosophy that makes a limited statement about the quality of a manufactured item when a direct measurement of the quality is not practical or not possible. The strategy originated from the *Big Data–Big Model* (*BDBM*) point of view described in [3] that was used to develop an initial quality monitoring process for the ultrasonic welding of battery tabs in the Chevrolet® Volt. The strategy uses real time manufacturing process data to declare an item as either "good" or "suspect". Though the context of the development and application of PMQ were very specific, the potential applications are broader. Application of standard *SPC* has three requirements: a mature understanding of the process, an observable relevant quality characteristic with associated quality criteria, and a strategy and process to verify the quality criteria at the plant in real time. Today's innovative manufacturing environment and competitive business environment sometimes force the launching of a product even though the above three requirements for an *SPC* program cannot be satisfied. Fig. 1 shows how standard *SPC* is "brittle"; it "breaks" if not all steps are possible or not all steps are successfully completed. The purpose of this letter is to indicate how *PMQ* enhances and extends standard *SPC* by addressing three incomplete background knowledge situations that *SPC* or *traditional quality control* [8] cannot.

2. Background

SPC uses first principle knowledge, engineering technology, and statistical tools to control a manufacturing process under a well-understood cause and effect framework. When this framework is missing or incomplete, *PMQ* supplements it with an empirical predictive framework based on statistics, machine learning, and optimization. *SPC* requires known product quality characteristics that are measurable within the temporal and physical constraints of the manufacturing plant environment. Fig. 2 provides a taxonomy of quality features in manufacturing and relates them in a path diagram, which is list of the numbered nodes separated by an arrow, "→". The path that describes a conventional quality control initiative is $(1 \rightarrow \{3,4\} \rightarrow 6 \rightarrow 9 \rightarrow 12)$. This path relies on a quality characteristic that is known and physically observable either by

Abbreviations: BDBM, Big Data–Big Models; NDE, non-destructive evaluation; PMQ, process monitoring for quality; SPC, statistical process control; UMQ, usage monitoring for quality.

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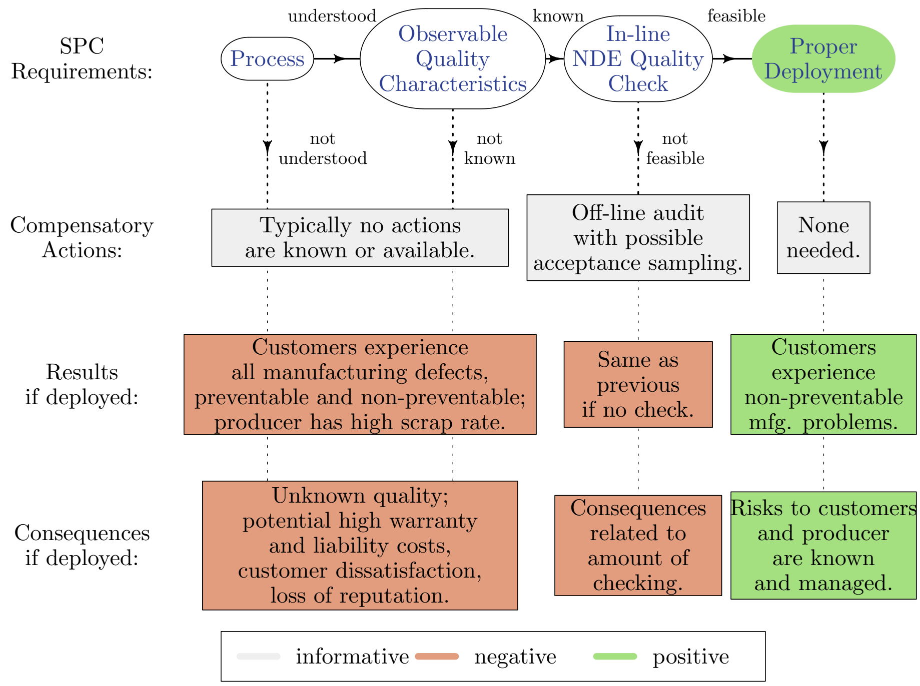

Fig. 1. Challenges to *SPC*.

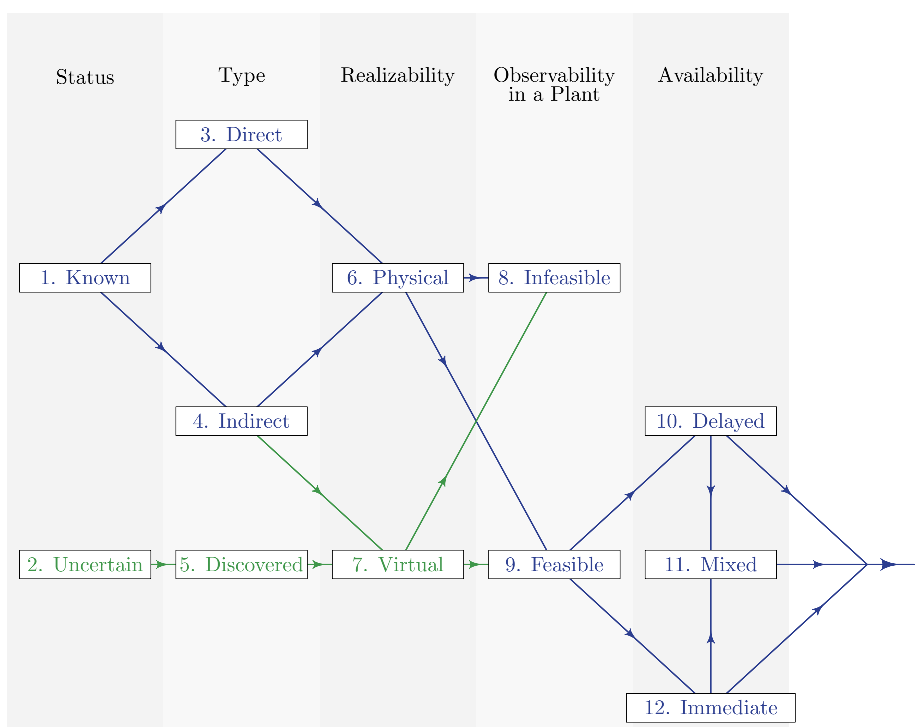

Fig. 2. Taxonomy of quality features in manufacturing.

direct or indirect means such that it is feasible in a manufacturing line and can immediately provide a good/bad quality status. Sometimes the characteristic cannot be measured directly. This situation can occur when the value of the characteristic involves destroying the item. When the characteristic cannot be measured directly, theory or engineering practice often provide a proxy through which the desired value can be obtained indirectly.

Even when a physical characteristic exists and is measurable, it may not be feasible to measure it within the time constraints of the manufacturing process. We call this the *infeasible measurement problem*: $(1 \rightarrow \{3,4\} \rightarrow 6 \rightarrow 8)$. The preferred scenario is for the characteristic to be measured immediately after the item is produced, $(1 \rightarrow \{3,4\} \rightarrow 6 \rightarrow 9 \rightarrow 12 \rightarrow)$. When there is a delay in the time of measurement and the buffer has a large capacity, all

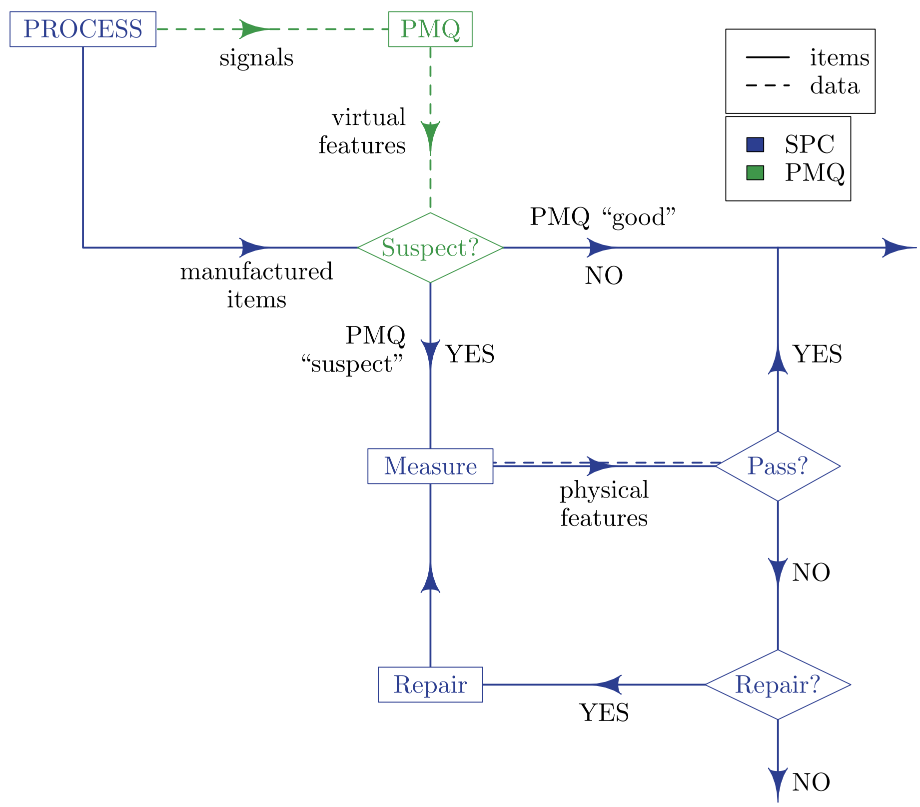

Fig. 3. *SPC* and *PMQ* quality control framework.

items in the buffer are suspect when a problem is detected at the measurement station. Extra time and expense are required to test and possibly repair or scrap the items. We call this the *delayed measurement problem*: $(1 \rightarrow \{3,4\} \rightarrow 6 \rightarrow 9 \rightarrow 10)$.

Development of a quality control procedure cannot even begin when the quality characteristic is "uncertain". When manufacturing is not allowed to commence until a quality procedure is in place, new product launches may be delayed and early-to-market advantage may be lost, even when the product has high quality. We call this the *uncertain characteristic problem*: $(2 \rightarrow)$. When manufacturers proceed anyway, they accept the consequences, Fig. 1.

3. *PMQ*-enabled opportunities and exercisable options

Conventional quality control is built on a mature knowledge of the product and process and a plant-capable measurement technology. *PMQ* is an extension of traditional *SPC*, Fig. 3, and it partially alleviates the three problems mentioned in the previous section. *PMQ* uses the *BDBM* style of thinking to extract features from signals and then to create binary classification models that declare items as "good" or "suspect". The feature creation and model building is usually done off-line to produce a rule[1] that is deployed on-line. Since the features and the rule are products of the *BDBM* learning algorithms, the resulting features are called "virtual" because essentially they are mathematical quantities designed for their predictive power, not their explanatory power. Hence, they may not have a direct physical interpretation. Virtual features can be thought of as "weaker" than the usual physical features, but the two together address the three stated problems and offer other possibilities.

[1] Whereas a classifier is a procedure for predicting the class of an item, we use the term "rule" to designate a procedure with all its parameters and unknowns completely specified so that it can be deployed.

The *delayed measurement problem* can obviously be avoided or eliminated by testing the item immediately after it is processed. When that is not possible, *PMQ* offers the possibility of creating a rule than can give an early warning of a problem so that the potential of a buffer full of defective items is diminished or eliminated.

PMQ provides two possible remedies for the *infeasible measurement problem*: (1) rely totally on the rule to declare an item as either "good" or "bad", when the classifier has the required false alarm (type I error) and miss (type II error) rates; and (2) use *PMQ* to reduce the number of items that must be measured, as it did in [3]. If the product has high conformance, a *PMQ* rule may be able to declare enough items as "good" so that the line rate is not affected while allowing the "suspect" items to be tested and then returned to the line when they are found to be in conformance. This strategy involves paths through the "Mixed" node (11) in Fig. 2.

PMQ enables *SPC* to commence even when theory and engineering practice do not provide a quality characteristic. This can occur when the technology is new and incompletely understood so that standards and specifications have not yet been developed. Typically some method of quality verification is available, otherwise management would not manufacture the item, but such a method is typically infeasible or impractical in some way: time consuming, inefficient, or costly. *PMQ* can address the *uncertain characteristic problem* in a manner similar to that in the *infeasible measurement problem*. The virtual features in the classifier can be used to reduce the number of items tested by the impractical method. The number of items that travel down the *PMQ* "good" path in Fig. 3 have to be sufficiently numerous to keep the line running and simultaneously to allow the "suspect" to be measured and possibly reinserted into the assembly line.

The virtual features and resulting rule play an important but auxiliary role in addressing the above three problems. Especially for the latter two problems, they may be seen as providing a temporary solution until sufficient knowledge has been acquired. The *PMQ* approach allows the manufacturing process to continue and still ensure quality for the customer without the usually required mature understanding of the product and process.

PMQ can enhance the quality movement in three other ways:

1. **Multiple testing** The *PMQ* rule can be used with the traditional quality test to form a new test comprised of two sub-tests: the first test using the virtual features and the second test using the physical features. A number of strategies are possible such as only retest the "suspects". The choice of an appropriate strategy and rule requires finding the error rates of the feasible retest–rule.
2. **Learning catalyst** *PMQ* can be divorced from the immediate process and be used for continuous learning about the process. This is helpful when the traditional theory based approach is not leading to further boosts in quality [9,10]. PMQ is founded on the principle of parsimonious modeling [13] which facilitates high-level information extraction through model interpretation. If applied to an appropriately acsensorized process, PMQ can serve as a catalyst to innovative ideas that can move the learning curve off the plateau of no progress.
3. **Usage monitoring for quality** *(UMQ) SPC* is often thought of as only an intra-plant activity, but the *BDBM* environment makes one realize that it is also an extra-plant activity because data on the performance of the manufactured item can be and are being collected on the item as it is used. From this point of view, a warranty event can be loosely viewed as a "failure" in the binary "success-failure" context of a plant. The hypothesis is that warranty data may provide some information about the role of the manufacturing process in creating the problem. The challenge is to link the warranty issue to the process via the signal data collected during the manufacturing of the item. Usage data are being used for maintenance scheduling, failure prediction, and product health management. The challenge is to extend the analysis to link usage data to the plant.

4. Summary and discussion

PMQ is an addition to *SPC*. It was made possible by the *BDBM* environment and is critical for value creation and success of future large-scale industrial applications. Modern plants generate large volumes of data from processes that are complex and not necessarily understood from the first principle perspective. This letter pointed out three situations, viz. the *delayed measurement problem*, the *uncertain characteristics problem*, and the *infeasible measurement problem*, where *PMQ* addresses what traditional *SPC* lacked. In fact, traditional *SPC* is "*Product* Monitoring for Quality" whereas *PMQ* stands for "Process Monitoring for Quality". *PMQ* uses measurements on the process and a learning strategy to create virtual features and a rule that identifies a large percentage of the good items. Unlike *SPC* [11,12], *PMQ* does not rely on the first principle understanding of the process though it is equipped to exploit any such knowledge. Instead of labeling "good" or "bad" like *SPC* would, *PMQ* calls "suspect" those items whose features have characteristics that differ from those in the training set. It could be viewed as a weaker classifier because its declaration of "suspect" is really equivalent to a declaration of "uncertain".

The *PMQ* classifier can be used as the first classifier in a multiple testing situation to either improve performance or to reduce the burden on subsequent classifiers. Model interpretation may provide new ideas and directions for process improvement.

Future Work

PMQ may be extended to UMQ , where extra-process data are used to improve the manufacturing process. PMQ and its potential extensions give new meaning to and opportunities for continuous improvement in manufacturing.

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