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Using a classifier ensemble for proactive quality monitoring and control: The impact of the choice of classifiers types, selection criterion, and fusion process

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ABSTRACT

In recent times, the manufacturing processes are faced with many external or internal (the increase of customized product re-scheduling, process reliability…) changes. Therefore, monitoring and quality management activities for these manufacturing processes are difficult. Thus, the managers need more proactive approaches to deal with this variability. In this study, a proactive quality monitoring and control approach based on classifiers to predict defect occurrences and provide optimal values for factors critical to the quality processes is proposed. In a previous work (Noyel et al., 2013), the classification approach had been used in order to improve the quality of a lacquering process at a company plant; the results obtained are promising, but the accuracy of the classification model used needs to be improved. One way to achieve this is to construct a committee of classifiers (referred to as an ensemble) to obtain a better predictive model than its constituent models. However, the selection of the best classification methods and the construction of the final ensemble still poses a challenging issue. In this study, we focus and analyze the impact of the choice of classifier types on the accuracy of the classifier ensemble; in addition, we explore the effects of the selection criterion and fusion process on the ensemble accuracy as well. Several fusion scenarios were tested and compared based on a real-world case. Our results show that using an ensemble classification leads to an increase in the accuracy of the classifier models. Consequently, the monitoring and control of the considered real-world case can be improved.

1. Introduction

The growing need for complex and customized products and services has led to increased complexity of the associated manufacturing processes as well; this complexity may be attributed to several different sources depending on the features of the product/service and the organizational structure of the companies. Consequently, the manufacturing and control tasks become difficult, including their monitoring and quality management. Despite the many methods and operational tools that have been developed in the last few decades, the executive management personnel of these companies are always seeking new approaches and tools to analyze their specific problems and devise potential improvement strategies at several levels. These approaches and tools can thus be regarded as decision-aiding tools to identify not only the root causes of defects but also factors critical to the quality of their products/services; in particular, the aim of the executive managers is to eliminate those causes or limit their impact by setting the factors critical to quality at adequate or optimal levels. Among these approaches, a common method is the Design of Experiments (DoE); however, the primary disadvantage of such an approach is that the improvement process is considered "off-line." Indeed, even if a robust process is established by successfully optimizing the controllable and uncontrollable factors, this approach remains static, unable to take into account large and lumpy variations of all related factors throughout the process life cycle. Therefore, to handle these variations, online monitoring approaches are required. Moreover, in modern industries, many companies have adopted digital transformation, facilitated by recent technological advances in the field of communication and computer science, consequently, leading to the generation of large amounts of data from the manufacturing processes and from different assets, such as machines, products, and plants; this poses a challenge to utilize these data dynamically to monitor and manage the quality of these processes.

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Thus, machine learning is considered a suitable alternative to address this situation.

Furthermore, this paper reports on a study conducted in collaboration with a furniture company faced with some critical quality problems owing to the complexity of product flows because of considerably customized products with different routing sheets, as well as the complexity of some manufacturing processes, many of which are based on uncontrollable factors, including temperature, pressure, and their interactions. Previous research [1] has demonstrated the significant advantages of an online quality monitoring approach based on defects classification using the neural network model; in addition, the research has highlighted some interesting perspectives, for example, improving the accuracy of the classifiers used. The primary aim of our study is to improve the accuracy of these classifiers. In this study, we primarily consider continuous data, and in this context, the most suitable classifier types are logic-based algorithms, neural networks, instance approaches, and support vector machines (SVMs). Nevertheless, these tools lead to classifiers with varying performances. Considering this, two approaches could be used: either selecting the classifier that yields the best results on a validation dataset or constructing a committee of classifiers to take advantage of the diversity of combined classifiers; the second approach is based on the hypothesis that a committee of classifiers, in general, outperforms its members [2]. This committee of classifiers is known by several names such as committees of learners, mixture of experts, classifier ensembles, and multiple classifier systems [3].

Classifier ensembles are often built using only one type of classifier; for example, neural network (NN) ensembles [4,5], SVM ensembles [6,7], k-nearest neighbor (kNN) ensembles [8,9], or tree ensembles [10–12]. Santucci et al. [13] have driven this approach to the extreme case because they proposed building a classifier ensemble based on one unique model by varying its parameters.

Wozniak et al. [3] proposed a survey on multiple classifier systems and suggested these systems for various applications, including remote sensing, computer security, banking, medicine, and recommender systems. Although in their study, Zhou et al. [14] used an ensemble of surrogates for dual response surface modelling, which is a regression problem, the application of classifier ensembles to production control problems and particularly to the quality monitoring problems has not been investigated.

Moreover, some authors used different types of classifiers in their applications [15,16]; however, to the best of our knowledge, there is no study on the impact of using different types of classifiers on model accuracy.

Therefore, to bridge these abovementioned gaps in research, we propose a methodological approach to build a classifier ensemble based on four types of classifiers, namely decision tree (DT), kNNs, multilayer perceptron (MLP), and SVM classifiers; in addition, we analyze the accuracy of proposed models on a real-world quality monitoring problem. In our study, we focus on the impact of the choice of classifiers types, the selection criterion, and the fusion process of the classifier ensembles. The best classifier (individual or ensemble) was selected to be implemented for the real application. Furthermore, the use of this classifier to determine the optimal setting of the controllable parameters is also presented.

The rest of the paper is organized as follows: Section 2 presents the related state-of-the-art methods and methodology for the classifiers used in this study and the construction of a committee of classifiers in general. The use of these classifiers to predict, and consequently, limit the incidence of quality defects is discussed in Section 3. Section 4 presents information about the application of our proposed classifiers for quality monitoring of a robotic lacquering workstation, wherein we compared the diversity and accuracy of the different techniques. In addition, some strategies for designing classifier ensembles were compared, and the optimal parameters for online quality were also investigated. Then, the use of classifiers to predict the incidence of defects and to determine the optimal setting of controllable parameters to limit defects incidence is illustrated on a real-world industrial problem. Although in this industrial application, 25 different types of defects may occur, our study focuses on only one of them. Finally, Section 5 presents the discussion and conclusion for this paper.

2. Related work

The goal of classifier algorithms is to use a dataset to develop a model that classifies different instances into appropriate classes [17]. Köksal et al. [18] presented a review of data mining applications for quality improvement. They classified these applications into four primary domains:

- Product and Process Quality Description (identifying and ranking the quality variables) [19–21],
- Quality Prediction, when quality may be represented with a real variable [22,23],
- Quality Classification, when the quality characteristics are binary nominal or ordinal [24,25],
- Parameter Optimization [26,27].

The problem considered in this study is related to the last two categories mentioned above. The concept used here in designing a forecasting system is to ensure that it is in line with a physical system (Fig. 1). In the case considered in this study, the forecasting model must predict the class (defect or no defect) as the output based on the parameter values collected from the real-world system. In addition, this forecasting model may be subsequently used to evaluate the decisions taken.

The design of the forecasting system is based on knowledge discovery and data mining composed of a dataset collection task (variables selection, data collection, and preprocessing) and data mining task (classifier type choice, classification of the dataset into learning and validation datasets, fitting of the model, and evaluation of the results). To improve accuracy of the classifier, a classifier ensemble may be used.

2.1. Methodology for designing the classifier ensemble

In the past decade, the classifier ensemble has been established as a significant research field [3]. The goal of the classifier ensemble is to combine a collection of individual classifiers that are not only diverse but also accurate. In particular, considerably accurate classification methods can be developed by combing the decisions of the individual classifiers in the ensemble based on some voting method [10]. A classifier ensemble can be built at four different levels [28], namely the data [29], feature [30], classifier, and combination levels [31]. The design of a classifier ensemble consists of two primary steps: the generation of multiple classifiers and then, their fusion [32]; this leads to two challenging issues; first, how to select the individual classifiers, and second, how to combine the selected classifiers.

The key to designing a successful ensemble is to ensure that the classifiers in the group are sufficiently diverse. The four most popular algorithms [33] for improving diversity are the bagging [29], boosting [34], rotation forest [35], and random subspace methods [30]. The bagging and random subspace methods are more robust than other

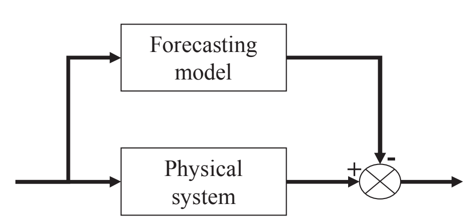

Fig. 1. Forecasting system in parallel with the physical system.