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Implantation of an on-line quality process monitoring

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Abstract— Because product quality level is today a key factor for companies' competitiveness and because it is really hard to control the manufacturing systems, there is a lot of scientific methods implemented on the shop-floor to improve quality at workstations. In our previous works, we have shown that the on-line quality control assisted by Neural Network seems to be a good alternative to the well-known industrial methods such as Taguchi Method. Nevertheless we have highlighted that a drift appears between the model and the process reality. In this paper, we propose a way to resynchronize the on-line control system behavior with it. This approach allows us to assure that the model stay robust and adaptable for the quality prediction. We will illustrate this with the Acta-Mobilier case, which is a high quality lacquerer company in the furniture industry.

Keywords— *Multivariate quality control; product quality; neural networks; Optimal Experimental Design; on-line control.*

I. INTRODUCTION

Because customers become increasingly demanding, quality control becomes increasingly important for companies. Indeed, even if there are policies such as Total Quality Management (TQM) in order to provide to companies the best way to control it, quality remains the number-one priority. Products are the only important bridge between the company and the customer and so, the first and main requirement is to send them with the exact wanted quality level. Moreover, the quality must always be controlled because it has a non-negligible impact on production processes.

However, despite all the available tools to control it, there are a lot of constraints that make the task extremely complex. The on-line quality control ensures proper reactivity and limits the production of non-conforming products. Taguchi Optimal Experimental Design (ODE) is one of the best ways to control quality at its source. For complex workcenters or on workstations subject to multiple constraints preventing the implementation of an ODE, we proposed a more computerized approach with an on-line quality monitoring system [12]. This approach is based on a neural classifier which learns from past production data the factors impact on defect occurrence. This

neural classifier is used to classify unknown quality patterns in order to perform an optimal tuning of process parameters.

However, because the manufacturing process evolves over time, it can drift very quickly from this static neural network model. To be able to control this quality monitoring system and to correct neural classifier, a control charts is used to highlight the drift.

In the next part, the quality monitoring issue is discussed. Part 3 presents the neural classifier used to control the product quality. At last, the classification results drift issue is discussed before to conclude.

II. QUALITY MONITORING

A. Why it is Necessary to Monitor Quality?

Quality is an important point of production processes for two reasons. First, the product quality is an important customer requirement. And secondly, quality control processes affect the productivity performance of the system [4]. This importance is underlined by the huge of methods to manage this quality. One of them is the SPC (Statistical Process Control) which assumes that, because the products are produced by processes whose behavior fluctuates over time and tend to become disorganized, companies need a preventive approach to bring up any process to a defined regularity level and to hold it by means of a monitoring system [13]. KAIZEN Methods are also efficient, unlike pure innovation, because they favor the gradual quality improvements (instead of large steps resulting from inventions) by continuous efforts on production processes and commitment [9].

Moreover, in the concept of Product Driven System, quality is a product attribute which will vary all along the manufacturing process. It is the product itself which is able, thanks to its own attributes (time, space, shape, quality level ...), to communicate with other products and machines in order to optimize its production process: i) each product, depending on its shape attribute, has one or several quality attributes; ii) each workstation, conveying devices or handling devices in the production system, affects all or part of product quality

attributes; iii) some values of quality attributes can produce modification in piece/lot routes (loops in the manufacturing process). That causes disturbances all along the production line. Indeed, following workstations would be starved (delay in manufacturing of defective products), whereas previous workstations would be saturated (previous step repetition to repair or make again the product). So quality is well a major factor of disruption of the product flow.

That is why, prediction and anticipation of the quality of the products is key elements of a well manufacturing process control.

B. Difficulties for Quality Monitoring

There are several ways to monitor quality and each way has advantages and drawbacks.

At the process level, each workstation modifies quality and shape attributes of products. So, quality control is required to be on-line at each location where this quality could be changed. These multiple control points (where it is possible to collect quality data manually or automatically) are the first binding point. This involves adding a multitude of non-value steps. In addition, to be effective in the collection and storage of data quality, computer support is also necessary and, therefore, we must also provide a wider deployment of Information Technologies (IT) on the workshop.

At the workstation level, Taguchi [19] was the first to propose, before the product manufacturing realization, a way to anticipate the quality through the adjustment and control of production system influent parameters. With his ODE, he was able to set up optimally the machine towards a quality objective. Taguchi method is a great complement of SPC [2]. Taguchi's Quality Engineering (TQE) policy leads to a more 5% quality level improvement [7]. But, as shown in our previous works, from the industrial point of view, an ODE is material and time consuming. These resources are sometimes not readily available because of their cost (expensive raw material or semi-finished product which may be degraded and therefore not sold) or utilization (bottleneck workstation). That is why deploying several ODE on each workstation which could have a significant impact on the quality level, is not necessarily conceivable.

On the other hand, the production process for a given workstation evolves over time. Indeed, many settings closely linked to the machine or its environment (as example, structure of the used raw material, weather conditions, machine wear...), induce variation. Previously cited techniques can facilitate and eliminate the main causes of variability in the production system [1]. But if one of the varying parameters influencing the product quality is not known by experts (and therefore not included in the monitored variables), the machine settings won't be optimal. Thus, for complex workstations or workstations subject to too many constraints, optimum setting could be unstable, too. So, quality can't be followed by a static model.

C. The Monitoring Quality Problem for the Company Acta-Mobilier

The company produces high quality lacquered panels made in MDF (Medium Density Fiberboard) for kitchens, bathrooms, offices, stands, shops, hotel furniture... With its certifications (ISO 9001, ISO 14001 and OHSAS 18001), the product quality is a constant preoccupation for Acta-mobilier. Manufacturing process is composed of several workshops. In these workshops, each workstation is likely to generate defects and the company has to include a quality control step there. This paper focuses on the robotic lacquering workstation according to the fact that it generates the main defects rate.

Even if this workstation seems free of human factors, the production quality is unpredictable (the risk of defect occurrence is unknown) and fluctuating (percentage of defects may vary from 45% one day to 10% the next day without changing the settings). It is too much costly to spend time to realize a Taguchi experimental design in order to improve this setting. Indeed, robotic lacquering workstation is considered as a bottleneck workstation and it is very hard to save time for the experiments. On the other hand, the cost of these experiments is very expensive because they consume semi-finished products (which have already a high added value).

III. ON-LINE QUALITY MONITORING SYSTEM

A. Généralities

"On-line" systems are generally essential in all industrial applications where decisions must be made in real time [10]. In such systems and due to its connectivity level, the "on-line" system is able to obtain, interpret and respond to the information received from its connected devices. Ideally, it can synchronize itself with the behavior of the real system. Many works underline the benefits of on-line approaches in many areas of research such as, for example, plasma spray devices [15], power transformer [18], CD [3]...

B. Initial On-Line Quality Monitoring System

Our goal is to prevent defects occurrence thanks to an on-line control system by performing set-up optimal parameters and by using quality monitoring model in considering actual production conditions. The quality monitoring process is designed by extracting knowledge on defects occurrence risk from the past production data. Psarakis [14] shows that, in a SPC process, Neural networks (NN) are able to improve the ability to automate the process, to detect and recognize more quickly and accurately the status of it.

For a traceability goal, data on defects and manufacturing conditions have been collected since February 2012 to September 2012. The initial quality monitoring system has been constructed by using this original database. Half of this data set was used to achieve the learning of 25 neural networks (1 per quality attribute seemingly predictable) while the other half was used to validate the obtained models. Chosen neural networks are Multilayers Perceptron (MLP) because Works of Cybenko [5] and Funahashi [8] have proved that, with only one hidden layer using a sigmoidal activation function and an

output layer, we can approximate all non-linear functions with the wanted accuracy. Its structure is given by:

$$z = g_2 \left(\sum_{i=1}^{n_1} w_i^2 \cdot g_1 \left(\sum_{h=1}^{n_0} w_{ih}^1 \cdot x_h^0 + b_i^1 \right) \right) \quad (1)$$

where x_h^0 are the n_0 inputs of the MLP, w_{ih}^1 are the weights connecting the input layer to the hidden layer, b_i^1 are the biases of the hidden neurons, $g_1(\cdot)$ is the activation function of the hidden neurons (here, the hyperbolic tangent), w_i^2 are the weights connecting the hidden neurons to the output one, b is the bias of the output neuron $g_2(\cdot)$ is the activation function of the output neuron and z is the network output. Because the problem is to obtain a probability of defect occurrence, $g_2(\cdot)$ is being chosen sigmoïdal.

In order to determine the number of hidden neurons, the learning starts from an overparametrized structure. A weight elimination method is used to remove spurious parameters [16]. The learning of MLP is performed in three steps: Weights initialization [11], learning of parameters by using Levenberg-Marquard algorithm with robust criterion [21] and weights elimination [18].

The resulting quality monitoring system (set of 25 neural classifiers) is embedded in the supervision tool of the lacquering workstation to be used by operators. The memory of these neural networks is physically remote in SQL database so that each independent program may access it if needed. This tool is a decision support system and it requires a human/machine interfaces as intuitive as possible. It is directly implemented in the set-up interface of the robotic lacquering workstation (Fig. 1.). Through this additional function, operator may, after entering production information (selected program, number of units produced...), assesses the risk of occurrence for a default (Fig. 2.). If the risk seems too large, he can change his production parameters (eg choose another program) and run the program in parallel to compare evaluation results until he obtains a satisfying result.

The current version of the on-line quality monitoring system takes, on average, 12 seconds to display the result. In 12 seconds, it has recovered the memory on SQL database, traveled the 25 neural networks and synthesizes the results

Fig. 1. Interface for collecting production data

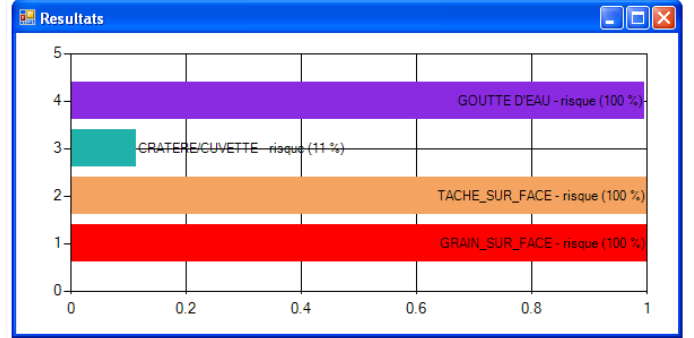


Fig. 2. The second reason concerns Defects occurrence risk

visually to facilitate interpretation by the operator, which means less than half a second calculation by neural network is needed.

However, shortly after its implementation, the answers provided by our system are no more coherent with reality.

C. Drift Evaluation

There are two apparent reasons leading our monitoring system to move away from reality. The first one concerns the evolution of input parameters. With a learning model, the learning outcome is valid only on the learned domain. The model is able to provide a valid solution only in this concerned domain.

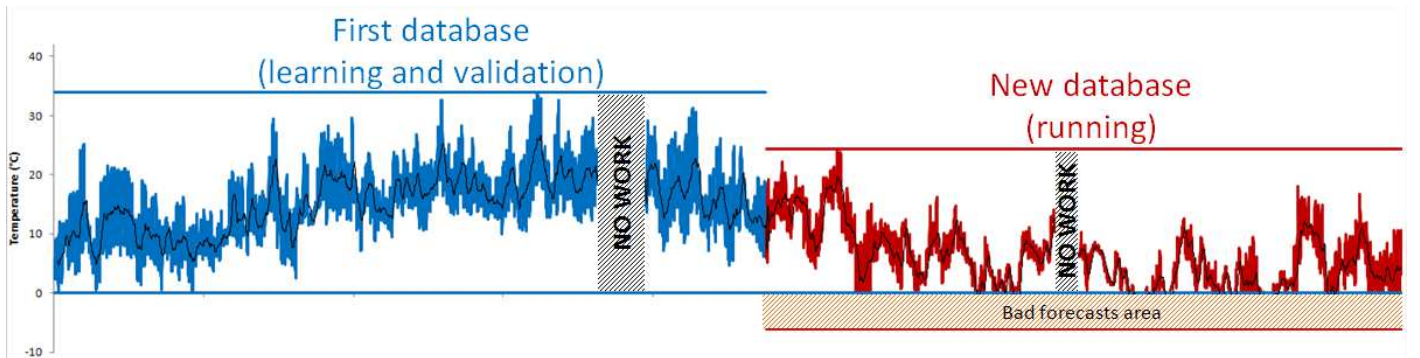


Fig. 3. Difference between learning domain and running domain

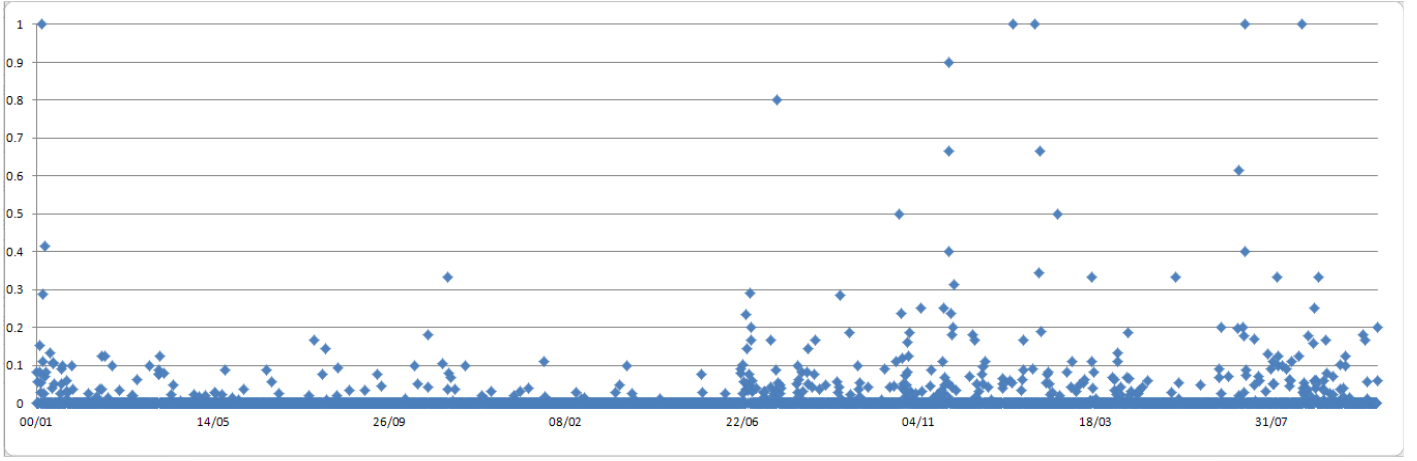


Fig. 4. Historic on grains on edges defect percentage

For example, in the new database, 446 data was collected between September 2012 and January 2013 and the exploitation of the quality monitoring process leads to 73% of non-detection and 32% of false positives for one of the 25 defects monitored. These poor results can be explained by the different process conditions between the two periods. As presented on the figure 3, in the first database, the temperature range varies between 0°C and 32°C when, in the new database, the temperature range varies between -5.2°C and 24°C . These negative temperatures represent 25% of the new database and correspond to an operating range of the process which is not learned in the quality monitoring process.

The second reason concerns the uncontrolled modification of the machine behavior. Indeed, by changing a parameter (voluntarily or not) which is not an input of the neural classifier, it is still possible that the behavior of the machine could be affected. In this case, we can conclude that this parameter should be part of the model inputs but, as it was considered constant for the duration of the learning step, it was not retained as such. Since this change, which may even be unknown to the operators and managers, the model will therefore provide results out of step with reality.

For example, on the figure 4, we can clearly realize that the studied defect rate (grains on edges) increases sharply after June, 22. The capitalized data from the machine environment does not allow knowing if there is a change in a forgotten input influencing parameter or if the actual use domain is too different from the learning domain.

Because it is not always possible to control changes in production parameters (uncontrollable one, weather, unanticipated change from the operator...), it is necessary at least to be able to detect them. By giving to the quality monitoring system the ability to verify its hypotheses by being kept informed on the reality, we can give it the ability to recognize its failure and thus to react accordingly.

IV. HOW TO CONTROL THE QUALITY MONITORING SYSTEM

A. Generalities

The monitoring of the quality system is a question of its synchronization with the reality. Because this synchronization is time consuming (a revision of the model can take from several minutes to several days), we have to optimize the synchronization frequency. Rather than consider a resynchronization frequency in response to events (arrival of new information from one of the connected devices, solicitation by an operator, etc...) or a periodically one (every hour, week, etc...), it is better to rely on statistical findings. Among the 7 basic tools for quality control, control charts, also known as Shewhart charts or process-behavior charts [17], are interesting Statistical Process Control (SPC) tools useful for our proposed system.

B. Control Charts

Control charts are particularly relevant to the dynamic quality control with the use of time-series data [20]. They can determine statistically if variation is no longer under control. Indeed, it is known that even when a process is under control there is approximately a 0.27% probability of a point exceeding 3-sigma control limits (Pareto). These few isolated points should not trigger synchronization. But too many points will be detected and underline the presence of a special cause, even if it is not yet known.

Combine the neural network with the control charts can therefore consider both the robustness of the statistical analysis and adaptability of the neural network. Li Du [6] has working on the inverse combination of both tools with a recognition algorithm of control charts using neural networks for getting alerts in case of quality problems and providing clues to define causes.

C. Control Bounds

Our control charts (p-charts) aims to determine if the misclassification rate (non-detection and false alarm) increases. The center line (CL) is given by the percentage of misclassified

data on the validation data set. Only the Upper Control Limit (UCL) are considered here and calculated for representing 95% and 99.8% of data. These limits are given by:

$$UCL_{99.8\%} = p + 3\sqrt{\frac{p(1-p)}{n}} \quad (2)$$

$$UCL_{95\%} = p + 1.96\sqrt{\frac{p(1-p)}{n}}$$

where p correspond to the center line (CL) and n to the size of the sample.

The Lower Control Limit (LCL) are presented on the figures but not used. The figure 5 presents two control charts performed on the new data where the sample size is set to 100 values, which corresponds to slightly less than one week of production. The dotted line corresponds to a control charts without relearning. We can see that the quality process is under control for both samples 1 and 4 but not under control for sample 3 and for the sample 2 the results are between UCL95% and UCL99.8%. This is due to the new operating range detected in the data as explained in the previous part. So the quality monitoring process must be improved. This is done by relearning of the neural network by using data of the two first samples. The initial structure and weights of the network are those given by the original quality monitoring process, so no pruning phase is needed. The initial weights are close to the optimal ones. So, the relearning phase is fast and needs few iterations. In the considered case only 8 iterations are needed to achieve the learning. That means a great saving of time.

The solid line represents the control charts when a relearning is performed after the second sample. This charts show that the relearning allows adapting the quality process monitoring to the new operating range. Results on the sample 3 are greatly improved without degrading those on the sample 4 (small improvement). This approach allows determining if an adaptation of the quality process monitoring is needed without using systematic relearning.

V. CONCLUSION

Quality has a significant impact on the production process. Being able to control it is an important issue in companies. The company Acta-Mobilier allowed us to deploy an on-line quality monitoring system on one of its most critical workstations: the robotic lacquering workstation. Thanks to a neural classifier system, it becomes possible to predict the occurrence of defects. But its predictions were quickly removed from reality, especially because the use domain is not superposed on the learning one and because of unforeseeable changes in the working conditions of the machine. To solve this problem, we have proposed a self-control of its predictions based on the statistical theory of control charts to give it the opportunity to start their own resynchronization and thus ensure the reliability of forecasts. This new capability makes it adaptable to manufacturing process changes and allows it to adapt to new input data domains.

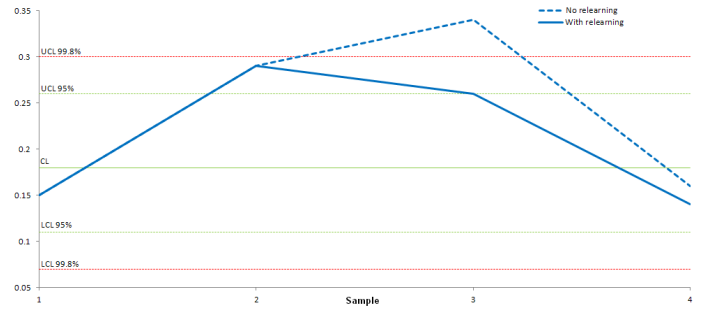


Fig. 5. Control charts with and without relearning

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