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A digital twin based method for the design and evaluation of sampling plans in a part manufacturing mill

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***Abstract* –Sampling process is an important quality control method for a lot of manufacturing companies, especially when the quality of the products is critical to their success. However, defining a sampling plan for a process that does not follow an independent and identically random distribution as the normal distribution can be challenging. In the industrial case presented in this article, we are indeed facing such a problem, which makes traditional sampling methods unusable. Nevertheless, one can use a digital twin based on real algorithms used in the process to analyze possible sampling plans. This article presents a novel data-driven approach to simulate the outcomes of applying possible sampling plans in the context of a high-precision metallic parts machining when facing non-normally distributed and correlated data. Based on historical production data, this approach is used to explore *what-if* scenarios, allowing sampling plans improvement and better process knowledge. In the wake of the Industry 4.0 movement, data-driven digital twins are the first stepping stone towards more intelligent and adaptive models.**

***Résumé* – Les processus d'échantillonnage sont une méthode de contrôle qualité très importante pour beaucoup d'entreprises manufacturières, particulièrement lorsque la qualité des produits est critique pour leur réussite. Par contre, la définition de plans d'échantillonnage peut s'avérer ardue lorsque nous faisons face à un procédé non identiquement et indépendamment distribué de façon aléatoire. Dans le cas d'étude industriel présenté dans cet article, nous faisons face à cette situation, rendant les méthodes d'échantillonnage traditionnelles inutilisables. Cependant, il est possible d'utiliser un jumeau numérique basé sur les algorithmes réels utilisés dans le procédé pour analyser des plans d'échantillonnage potentiels. Cet article présente une approche basée sur les données qui permet de simuler l'application d'un plan d'échantillonnage dans un contexte d'usinage de pièces métalliques de haute précision. L'approche utilise des données historiques de production (non normalement distribuées ni indépendantes) pour explorer des scénarios d'hypothèse, permettant une amélioration des plans d'échantillonnage et une meilleure connaissance du procédé. Dans une époque où l'Industrie 4.0 prend de plus en plus d'importance, la conception d'un tel jumeau numérique basé sur les données est la pierre angulaire afin d'obtenir des modèles intelligents et adaptatifs.**

***Mots clés* – Échantillonnage, simulation de procédé, jumeau numérique, procédé d'usinage, Industrie 4.0**
***Keywords* – Sampling, process simulation, digital twin, machining process, Industry 4.0**

1 INTRODUCTION

The manufacturing sector faces many challenges regarding quality control processes, which are responsible for a significant part of the production costs, in addition to being critical for legislative aspects [Schiffauerova and Thomson, 2006]. For a lot of businesses in the manufacturing sector, the inspection of all produced parts would represent considerable and costly efforts, which also requires an important time. In those cases, sampling methods are used to select a certain quantity of products for quality control purposes.

More precisely, the sampling rate is what will drive the level of effort to control the quality of the product manufactured. In the past decades, a lot of research efforts have been made in studying different methods of sampling products amongst production lot [Dauzère-Pérès and *al.*, 2010; Dodge and Romig, 1929; Fallah Nezhad and Nesaee, 2021; Kogan and

Raz, 2002; Lieberman and Resnikoff, 1955; Negrin and *al.*, 2011; Nesaee and Nezhad, 2021; Pearn and Wu, 2006; Yu and *al.*, 2012]. Historically, those methods were designed to be static, meaning that they were assuming a normal and independent distribution of the quality features that were inspected, either they had a known or unknown standard deviation (see [Lieberman and Resnikoff ,1955]).

For processes that do not follow traditional rules of statistics as the normal distribution, the application of standard sampling methods can become problematic and incoherent as the assumption of normality can sometimes cause discrepancies in the rejection percentage when sampling lots of parts with the methods (see Das and Mitra [1964]).

As an example, for a milling plant, each time a part is measured some adjustments are made to the manufacturing process (e.g. adjusting the position of a tool in a CNC machine to compensate for tool wear). Therefore, normal distribution and/or independent distribution hypotheses are not met.

We propose using a digital twin in such contexts. The digital twin must integrate (1) the real algorithms used by the company to adjust production parameters after a part is measured; (2) empirical data from past production runs, and (3) the ability to determine how changing those production parameters impacts future parts measurement. Using this, we can evaluate how changing the sampling plan impacts production quality.

Moreover, the approach allows the process owners to have a better understanding and a better managerial insight of the sampling process, i.e. how the process affects the overall quality but also the resources and equipment utilization. This approach is then applied to an industrial case, more precisely on a high-precision metal part sampling process.

The remaining of this article is organized as follows. To have a better sense of the limits of traditional sampling methods applied to manufacturing processes, a literature review is conducted (Section 2). Then, a description of the actual sampling process of the company, as well as on the availability of historical production data is presented (Section 3). This leads to the digital twin and simulation approach which can be used to make *what-if* scenarios based on theoretical sampling plans (Section 4). Finally, a conclusion on the next phases of this project will be found in Section 5.

2 Literature review on Sampling methods

The method used to conduct the review on sampling methods was based on the hermeneutic circle developed by Boell and Cecez-Kecmanovic [2010]. The keywords used to conduct searches in the Web of Science database [Analytics, 2020] were mainly *sampling*, *lot sampling* and also *computer experiments*, while the search was refined each time by exploring the cited works, as defined in the hermeneutic circle method.

One of the first to study which looked at sampling methods for an industrial process was from Dodge and Romig [1929]. In this research, Dodge and Romig introduced for the first time the concept of consumer's and producer's risks, which are largely used in today's methods to determine the lot inspection rate. A few years later, Lieberman and Resnikoff [1955] defined what is today considered the basis for quality control based on the sampling of a population. The authors thus defined methods to determine the sampling rate based on the standard deviation, whether it is known or not among the population, and based on the mean range of the values inspected.

In 1964, Das and Mitra [1964] studied the effect of non-normality on acceptance sampling plan, which is usually based on normal distributions. Thus, the authors studied the effect of these assumptions on lot rejection and acceptance probabilities with respect to consumer's and producer's risks. In their conclusions, the authors pointed out that making normality assumptions with non-normal distributions can cause significant distortions in rejection and acceptance rate, particularly for plans that require large sample sizes and when the specifications for inspection are very strict (which is the case for high-precision machining).

Kogan and Raz [2002] addressed the problem of defect detection and inspection intensity in a general context of project management. The authors used historical data to model the defect arrival rate for each phase of the project, the defect detection rate as a function of the inspection efforts and all the costs related to the remaining defects and to these inspection efforts. Using traditional integral calculus, the authors defined the optimal inspection intensities for each type of defects and each phase of the project. As the computational resources increased over the years, so did the complexity of the models developed in this field of expertise. Lee [2002] used a self-organizing map (SOM), which is a specific method from the supervised machine learning techniques, to determine the optimal inspection locations to maximize the defect detection rate. In their work on the "wafers at risk" ("W@R"), Dauzère-Pérès and *al.* [2010] used simulations to model a wafer manufacturing process where a theoretical set of wafers are inspected and the simulated number of wafers at risk is measured. To find the optimal set of wafers to inspect, the authors simulated the W@R for all permutations. However, one could say that this approach can only work if the simulation model is not too much time-consuming. Pearn and Wu [2006] used the Taguchi process capability index (Cpm) to design a sampling method that considers the producer risks as well as the consumer risks. According to the authors, the Taguchi capability index emphasizes measuring how well a process can cluster a certain variable around a defined target. Similarly, Negrin and *al.* [2011] explored the possibility of using a process performance indicator, the process capability index (Cpk), to develop a multi-level method of sampling products for inspection. In addition to the Cpk, the authors used the coefficient of determination (R^2) to evaluate what they call "the gain due to expectation"; the more to process is stable, the more they can predict the process outcome, and the less they need to inspect their products. Fallah Nezhad and Nesaee [2021], as for them, reviewed and studied the use of EWMA statistics (*exponentially weighted moving* average) in sampling methods. More precisely, the authors developed a double sampling plan based on the EWMA of previous lots sampling but also on the producer's and consumer's risks level. The authors demonstrated that their method allows to decrease the average sample number comparatively to a single sampling plan based on the same EWMA.

From what was discussed in this section, we can conclude that there is space for more research in the area of product sampling for a complex manufacturing process. Indeed, from what we know so far, the manufacturing sector is still largely using traditional and conventional sampling methods as defined in standards like the well-known MLT-STD-105E [USA, 1989] or the ASTM's standard [International, 2018]. The former standard defines basic sampling methods based on various parameters like the AQL (a*cceptable quality level*) and the inspection severity, as well as some useful tools for conducting inspections. As for the latter, the ASTM standard on sampling, it presents basic sampling methods based on probabilities and inspection guidelines based on internationally recognized inspection principles.

Yu and *al*. [2012] studied the use of active learning schemes proposed by MacKay [1992] and Cohn [1993] in order to measure the reduction in the predictive variance over a particular design space and choose the points that maximize this reduction of variance. More precisely, their work aims to improve the way computer simulation of design points are done and how these design points are selected, allowing parallel computing in a very large design space. As an example, for a possible use of their method, the authors mentioned the processor manufacturing industry, where the processors design space is often composed of many design points. On that note, it appears that the study of the use of multilevel control plans are rather scarce, and even more for the use of dynamic control. Considering a variable process, one can suppose that an adaptive method to define control and inspection plan would increase the overall quality and the overall inspection cost of a manufacturing process, as observed in Negrin and *al*. [2011], Nesaee and Nezhad [2021] and Pearn and Wu [2006]. Furthermore, the use of multilevel or dynamic control plans, from what we can see in the literature, considers the quality assurance perspective but not so much in the process control aspects, for instance in the case of a process using a sampling process as a feedback loop. When facing a process where a systematic quality control process does not appear to be viable nor desirable, we can stipulate that the design of the sampling plan is critical to many aspects of the process performance: the lead time of the machined lot, the average quality of the parts, the defect detection rate, and many more.

The subject of sampling in the context of Industry 4.0 has not been extensively discussed in the literature. However, some authors have nonetheless studied the question. In their work on sampling strategies for surfaces of machined parts, Moroni and Petrò [2018] define three types of sampling methodology; blind, manufactured-based and adaptive sampling strategies. Blind sampling strategies are based on theoretical information and could be considered as Industry 3.0 sampling strategies. The use of adaptive sampling strategies is the kind of strategies one would see in an Industry 4.0 manufacturing process, still based on theoretical information. The manufactured-based sampling strategies are data-driven but require models of the process investigated, which can be a very challenging task. It is relevant to mention that surface sampling is quite different from lot and feature sampling but share nonetheless some similarities for data points selection.

On that note, some authors mentioned the importance of having adaptive decision-making models in the context of intelligent manufacturing [Zhong and *al.* , 2017]. Kagermann and *al*. [2013] underlined the importance of having models for managing complex systems. These models would fulfill two distinct roles, namely planning operations and explaining systems (planning models and explanatory models as mentioned by the authors).

To get a sense of the evolution of the sampling methods over the last decades, Table 1 presents a brief summary of the different works discussed until now.

3 INDUSTRIAL CASE STUDY AND DATA

The case study investigated at APN Global is related to the machining industry, more precisely the turning process for the manufacturing of high-precision metallic parts used in the assembling of aircraft engines and gas chromatographic analysis devices. These parts can have up to about 70 features that need to be checked to make sure to have a valid part that meets the standards. These features consist of part dimensions, holes depth, diameters and circumference, angles, holes positioning, as well as other positioning features. APN Global has instigated a digital transformation a few years ago, which at some point allowed the company to improve its data gathering concerning different parts of the manufacturing process.

3.1 Sampling plan

The rate of inspection is not the same depending on the feature. For instance, a feature which is known by experts to be highly variable and unstable could be inspected more often than others. There exist different inspection methods: (1) conventional optical comparator, (2) numerical and automated optical comparator, (3) manual using gauge pins, precision calipers and other traditional metrological tools. For each feature of a particular part, the *sampling plan* dictates when to inspect a particular part, which features, and which inspection method to use.

Defining the optimal sampling plan is not straightforward. Although quality is important, we cannot afford to measure everything. The optimal sampling plan is the one that prevents parts to fall out of specifications, but with the least possible costs. Indeed, the costs generated by the inspection process are important. Except when the measurement is taken manually or with an optical comparator, a part that needs to be measured has to be moved, manually or with the help of an automated guided vehicle (AGV), to the inspection equipment (CMM). With the addition of the corresponding inspection time, the delay between the end of a part machining and its inspection is variable so the inspection process can be a bottleneck. At the moment, the sampling plan is defined by quality assurance experts who need to analyze previous manufactured batches manually in order to define an appropriate sampling rate for every feature of a particular part. For that reason, using a digital twin to study the effects of changing the sampling rates can be beneficial from a quality control perspective.

3.2 Offsets/corrections

Over time, a drift in part measurements may appears (e.g. because of tool wear) so corrections are applied to stabilize the process and keep the parts compliant. These corrections are also called *offsets* and they are represented as 4-axis temporary displacements (*x*, *y*, *z or r*[1]) of the tools used.

[1] Expresses a radius.

Table 1. Summary of the literature on sampling methods.

Author	Application	Objectives	Conclusion of the authors	Applicability of the method to the research problem
Dodge and Romig [1929]	Generic	Study and definition of the concepts of consumer's and producer's risk in lot inspection, concepts that are largely used in traditional sampling methods	According to various levels of risk, the authors developed charts and graphs allowing the users to define the acceptance number, sample size, and minimum amount of inspection per lot	The proposed method is used to determine if a lot should be accepted based on the inspection of a few samples and not in the context of a process control of multi-featured parts
Lieberman and Resnikoff [1955]	Naval parts inspection	Define sampling methods based on known standard deviation, unknown standard deviation, and mean range of the values inspected	The authors defined methods that are still considered today as the basis for quality control of part lots and sampling	The authors had the assumption that the sampled variables are independent, identically distributed normal variables
Das and Mitra [1964]	Generic	Study the effect of normality assumptions on acceptance sampling plan for non-normal distribution	The authors proved that there are significant distortions on acceptance and rejection rate when normality assumptions are wrongfully made	No method is presented in this article. The authors outlined the difference of assuming incorrectly a normal distribution
Kogan and Raz [2002]	Software development	Tackle the problem of defect detection and inspection intensity in a project management	Based on historical data, the authors used traditional integral calculus to determine the optimal inspection intensity	The analytical method proposed by the authors is specifically designed for defining inspection points when managing a project
Lee [2002]	Wafers manufacturing (semiconductor)	Using a metric called *wafers at risk*, develop a method to define the optimal inspection locations to maximize defect detection rate and meet *wafers at risk* constraints	The use of machine learning, more precisely a self-organizing map, allowed the authors to significantly increase the defect detection rate	The method focuses on defining the sampling locations on the wafers, which cannot be applied to machined parts with multiple features
Dauzère-Pérès and *al.* [2010]	Wafers manufacturing (semiconductor)	Using a metric called *wafers at risk*, develop a simulation model permutating different combinations of inspected products	With their method, the author succeeded in cutting the average number of *wafers at risk* by half, and decreasing significatively the time *wafers at risk* spent above the warning limits of the process control chart	The method focuses on defining the sampling locations on the wafers, but cannot be applied to machined parts with different features
Pearn and Wu [2006]	Generic	Design a sampling method based on the Taguchi process capability index (Cpm) that considers the producer's and consumer's risk	The authors designed an inspection procedure based on the Cpm that considers the consumer's and producer's risk	The authors had the assumption that the sampled variables are independent, identically distributed normal variables
Negrin and *al.* [2011]	Generic	Define a multi-level sampling method based on the process capability index (Cpk)	Using the coefficient of determination (R^2), the authors developed a multi-level sampling method that analyses the information gained due to expectation which allows its user to decrease the inspection rate when he successfully predicts the inspected values	The authors had the assumption that the sampled variables are independent, identically distributed normal variables
Yu and *al.* [2012]	Computer processor design	Study the use of active learning schemes in design space exploration to improve the efficiency of computer simulation	Using two active learning methods proposed by MacKay [1992] and Cohn [1993] to measure the reduction of a predictive variance, the authors developed a method of sampling points in a very large design space	The method proposed by the authors implies to fit a predictive model to approximate the design space, which is often unrealistic for real case studies
Moroni and Petro [2018]	Part machining	Study the sampling process modelling in Industry 4.0	The authors defined three sampling methods: blind strategies, manufacturing-based strategies, and adaptative strategies. Each kind of sampling strategies has an increasing level of intelligence and adaptability	The approaches mentioned by the authors are applied for defining inspection physical locations on machined parts, and not to define sampling rates
Nesaee and Nezhad [2021]	Generic	Study the effect of having a double sampling plan based on the *exponential weighted moving average* (EWMA) of previous lot sampling	The authors concluded that having a double sampling plan allows its users to decrease the average number of parts sampled from a lot, and this for an equivalent amount of consumer's and producer's risk	The authors had the assumption that the sampled variables are independent, identically distributed normal variables

However, there exists some relationships between two or more features. When a specific tool affects two or more features of a manufactured part, the corrections applied to this tool to correct a feature may affect others too. In the following example (Figure 1), which represents a cross section of a fictional metal part, a change in the feature A will have an immediate impact on the feature B, and so will be the tool corrections generated during each lot manufactured. More precisely, if the measurement of feature B decreases, feature A will automatically increase, as the two features are linked. Knowing the relations between **all** the features, one can after any measurement(s) of any feature(s), compute the offsets that should be applied to the process. At APN, an algorithm (called the *Offsets computing engine*) automatically computes the new correction/offsets and applies them each time a measurement is carried on.

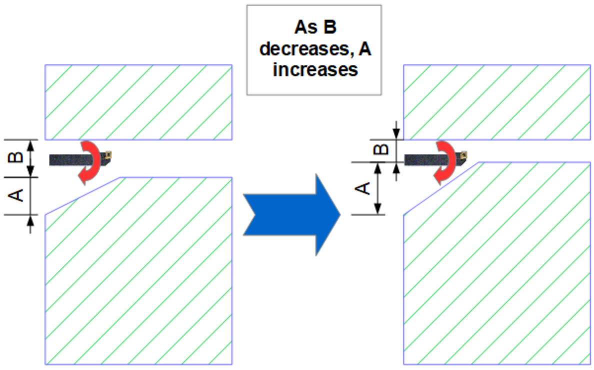

Figure 1. Cross section of a fictional metal part with a hole and a chamfered edge. Represents the effect of a change of one feature on another.

Therefore, the process is said to be “self-corrected”, which makes the part measurement distribution be well confined between control limits. Furthermore, these measurements are time series and dependant while they cannot be considered as normally distributed. For these reasons, traditional sampling methods as proposed by popular approaches like *Six Sigma* (see Pyzdek [2003] for more information) or normative organization cannot be applied since they generally assume normally and independently distributed data, i.e. there is no correlation between two measures at different times for the same feature.

3.3 Production historical data

The present case offers a very rich historical database, which can be used to design and validate a virtual tool that could be used as a digital twin to the actual sampling process. Then, with a predefined method to explore the design space, one can theoretically iterate on the digital twin and simulate which sampling plan would minimize the inspection effort while maximizing the overall quality of a lot of a specific part. Using this method allows one to overcome the problem of non-independently and non-identically distributed data mentioned previously.

Thus, the dataset used in the approach and extracted from this database consists of:

- All the information allowing users to identify each part of the batch, including the manufacturing time and date of the part;
- The inspected measurements of each feature for each part;
- The theoretical measurements of each feature for each part. These measurements are calculated with simple linear interpolations of inspected measurements;
- When the tools are changed;
- The accumulated offsets for each feature of each part.

However, one of the challenges of using this dataset is the fact that not every part of a batch is inspected and measured, which is why we have theoretical measurements of some features. At the moment, these theoretical measurements are computed with a linear interpolation, but some evidences show that this approximation is not accurate.

The data composing the dataset are acquired automatically and managed by an in-house manufacturing software. The

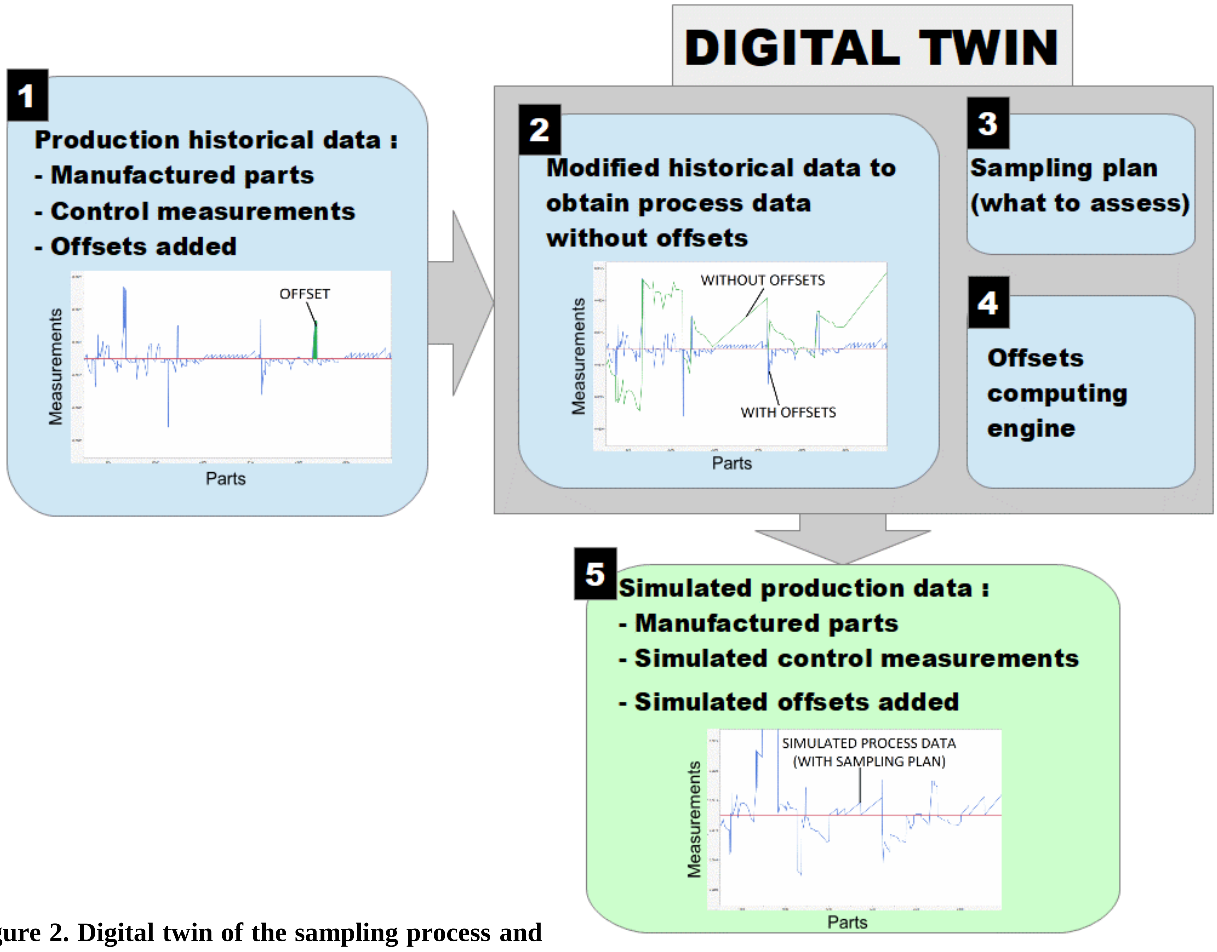

Figure 2. Digital twin of the sampling process and his components.

measurements are logged automatically when sent to the CMM cells or manually when a feature is measured by the operator or with the help of an optical comparator. It is relevant to mention that the dataset previously described has been standardized for multiple digital transformation initiatives.

4 DIGITAL TWIN FOR SAMPLING PLAN EVALUATION

The machining process is considered as a deterministic model that is a function of the sampling rate, since the number and the intensity of compensations are directly dependent on that sampling rate. Now consider the equation **(1)**: $g(\boldsymbol{x},\boldsymbol{y})=\boldsymbol{z}$, where $\boldsymbol{x} = [x_1, x_2, \ldots, x_j]$ is a 1x*j* vector that represents the sampling rate of the *j*th feature, $\boldsymbol{y}$ is a *i*x*j* matrix which represents the feature historical measurements for a particular product of the *i*th part and of the *j*th feature and $\boldsymbol{z}$ is also a *i*x*j* matrix which represents the value of the *j*th feature simulated measurement on the *i*th part of the manufactured lot. From these values, we can compute, for each part/feature combination, a deviation from the nominal value of the feature that was defined in the design process but also the theoretical number of noncompliant parts. These two quality indicators will eventually be used to compare different sampling plans as we can deduce from the equation **(1)** that these indicators are indirectly a function of the sampling plan in place and of the historical data used to do the analysis.

In order to achieve this level of computing, a digital twin of the sampling process was developed. Figure 2 presents this digital twin and its different components along with its required input and output. Let us detail a bit more each of these components:

The model is based on historical data (1). We know, for each part, which features were measured as long as their value. We also know the values of the computed offsets. As we have access to the real *Offsets computing engine* (4), we can modify the original data to remove the effects of the offsets that were carried on. This way, obtain have data (2) that shows how production would have derived if no offsets/corrections have been applied. Then, we can define any other sampling plan (3). Using simulation, we "replay" the production. Each time the sampling plan states some measurement must be carried on, we measure the features according to the sampling plan, call the offsets computing engine (4) and apply the offsets for the future parts.

From the resulting data (5), one can calculate various key performance indicators as the average measurement deviation per parts, the number of noncompliant parts or the number of part measurements that trigger a quality control warning.

As a fictional example, we could think of a part with two features, its length and width, for which we want to simulate the sampling rates of $\boldsymbol{x} = [x_1,x_2]$. The historical measurement could be $\boldsymbol{y} = [y_{11},y_{12},\ldots,y_{1N};\ y_{21},y_{22},\ldots,y_{2N}]$ where each measurement is either an inspected measurement or a theoretical measurement and where N is the total number of parts used in the historical data. In addition to these data, we also have a matrix of the same size as $\boldsymbol{y}$ that represents the cumulated historical offset, and we have a vector indicating when the tools associated with the two features are changed (step 1 of Figure 2). Now, we start by computing the measurement of each part and feature, without any offset, by subtraction of the historical cumulated offset (step 2). We then simulate inspection events, meaning which parts would be inspected considering $\boldsymbol{x}$ (step 3). Since the offsets are always the negative difference between the features' measurements obtained and the nominal values of the features, we deterministically apply offsets following the inspection events (step 4). Thus, we finally have simulated measurements for the two features mentioned previously of every part from the historical data that correspond to the matrix $\boldsymbol{z}$, which allows us to evaluate the performance indicators mentioned in the previous paragraph.

5 CONCLUSION

This article aimed at defining an approach to simulate what would happen if a different sampling plan was used in the context of a high-precision part machining process. Since the approach was designed for using historical production data, its application does not require any statistical premises as a normal distribution or uncorrelated data. This digital twin will undoubtedly be a valuable tool to determine optimal sampling settings at APN.

The use of models for complex manufacturing processes is one of the pillars of Industry 4.0 [Kagermann and *al.*, 2013]. Digital twins are the first step towards the design of more intelligent and adaptative sampling models, models that will eventually take into account the ever-changing parameters, conditions and performance of the machining process studied in this project. In our case, the digital twins presented as well as the future models will fulfill the role of a decision-making tool to analyze *what-if* scenarios. The full automation of the sampling plan definition process will however not be considered, as the quality of the product is too critical for the company's success.

One of the next steps will be to analyze the preliminary results in order to confirm the representativity of the dataset used and make sure that the data allow the model to be robust enough to work for different process conditions.

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7 REFERENCES

Clarivate Analytics. (2020). Web of science. https://www.webofscience.com/wos/woscc/basic-search

Boell, S. K. & Cecez-Kecmanovic, D. (2010). Literature reviews and the hermeneutic circle. *Australian Academic \& Research Libraries*, *41*(2), 129–144.

Cohn, D. (1993). Neural network exploration using optimal experiment design. *Advances in Neural Information Processing Systems*, *6*.

Das, N. G. & Mitra, S. K. (1964). Effect of Non-Normality on Plans for Sampling Inspection by Variables. *Sankhyā: The Indian Journal of Statistics, Series A (1961-2002)*, *26*(2/3), 169–176.

Dauzère-Pérès, S., Rouveyrol, J.-L., Yugma, C. & Vialletelle, P. (2010). A smart sampling algorithm to minimize risk dynamically. In *2010 IEEE/SEMI Advanced Semiconductor Manufacturing Conference (ASMC)* 307–310.

Dodge, H. F. & Romig, H. G. (1929). A method of sampling inspection. *The Bell System Technical Journal*, *8*(4), 613–631.

Fallah Nezhad, M. S. & Nesaee, M. (2021). Developing variables sampling plans based on EWMA yield index. *Communications in Statistics-Simulation and Computation*, *50*(4), 1135–1153.

International, A. (2018). *Standard Guide for Sampling Design*.

Kagermann, H., Helbig, J., Hellinger, A. & Wahlster, W. (2013). *Recommendations for implementing the strategic initiative INDUSTRIE 4.0: Securing the future of German manufacturing industry; final report of the Industrie 4.0 Working Group*. Forschungsunion. Chapter 5.

Kogan, K. & Raz, T. (2002). Optimal allocation of inspection effort over a finite planning horizon. *IIE TRANSACTIONS*, *34*(6), 515–527.

Lee, J. H. (2002). Artificial intelligence-based sampling planning system for dynamic manufacturing process. *Expert Systems with Applications*, *22*(2), 117–133.

Lieberman, G. J. & Resnikoff, G. J. (1955). Sampling Plans for Inspection by Variables. *Journal of the American Statistical Association*, *50*(270), 457–516.

MacKay, D. (1992). Information-based objective functions for active data selection. *Neural Computation*, *4*(4), 590–604.

Moroni, G. & Petrò, S. (2018). Geometric inspection planning as a key element in industry 4.0. In *Proceedings of 3rd International Conference on the Industry 4.0 Model for Advanced Manufacturing: AMP 2018 3* 293–310.

Negrin, I., Parmet, Y. & Schechtman, E. (2011). Developing a model-based sampling plan. *Quality and Reliability Engineering International*, *27*(8), 1183–1198.

Nesaee, M. & Nezhad, M. S. F. (2021). Designing variables sampling plans based on the yield index Spk. *Communications in Statistics - Theory and Methods*, *50*(3), 507–520.

Pearn, W. L. & Wu, C.-W. (2006). Variables sampling plans with PPM fraction of defectives and process loss consideration. *Journal of the Operational Research Society*, *57*(4), 450–459.

Pyzdek, T. (2003). The Six Sigma Handbook: The Complete Guide for Greenbelts, Blackbelts, and Managers at All Levels, Revised and Expanded Edition.

Schiffauerova, A. & Thomson, V. (2006). A review of research on cost of quality models and best practices. *International Journal of Quality \& Reliability Management*.

USA, D. of D. (1989). Military Standard MIL-STD-105E. Sampling procedures for inspection by attributes.

Yu, Q., Li, B., Fang, Z. & Peng, L. (2012). Model guided adaptive design and analysis in computer experiment. *Statistical Analysis and Data Mining: The ASA Data Science Journal*, *5*(5), 399–409.

Zhong, R. Y., Xu, X., Klotz, E. & Newman, S. T. (2017). Intelligent Manufacturing in the Context of Industry 4.0: A Review. *Engineering*, *3*(5), 616–630.