ON THE ROBUSTNESS OF THE METHODOLOGY FOR MODELLING THE DEPENDENCIES BETWEEN CIRCUIT AND TECHNOLOGY PARAMETERS OF INTEGRATED CIRCUITS

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*The impact of the manufacturing process variation on the integrated circuits (ICs) performance is an acknowledged topic concerning the semiconductor industry, yet not determined in a quantitative manner. Assessing it as early as possible in the design and production flow, i.e. in pre-silicon stage, under the form of a mathematical relationship, will enhance manufacturer's ability to improve production. Towards this goal, our previous work concentrated on developing the Verification for Manufacturability by Modelling Process Variation - Circuit Performance Dependency (subsequently named as **P2P4M**) methodology* [1] *capable to model the dependency of the device performances with the influential technology parameters by using Monte Carlo simulations.*

*Given the stochastic nature of the Machine Learning algorithms employed in the methodology, it is important to investigate if the **P2P4M** methodology returns coherent results at different runs. This paper presents a comprehensive analysis on the **P2P4M** methodology, both in terms of consistency and reliability. To this end, the evaluation concentrated on its capability across datasets, based on several metrics defined for this purpose. The results obtained on an Infineon Technologies product represent a trustworthy and comprehensible tool for both the designer and the technologist.*

Keywords: Process Control Monitor parameters, process variation, P2P4M methodology, integrated circuits performance

1. Introduction and Related Work

In the semiconductor industry it is crucial to maintain the highest possible standards in what regards the electrical performance of the IC products,

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given the inherent fabrication process variation. Moreover, considering the exponential complexity increase, as well as the constant dimension decrease [2], their performance became even more vulnerable to the slightest deviation from their nominal value [3].

In the same time, it is equally important to efficiently control the process variation and to accurately understand and predict the intricate impact of the process variation on the IC performance, in order to increase manufacturer's capability of mass production. On a broader scale, this can be translated as identifying the mathematical representation of the complex relationship between manufacturing and design, very early in the development phase (i.e. during pre-silicon - preSi).

The key to solving this problem may be the Process Control Monitor (PCM) parameters employed by the technologist to supervise the manufacturing process [4], such that any process variation is rapidly signaled. The PCMs' potential is huge, since the PCM structures are placed among the productive dies, which offers them the advantage to have the same technology steps applied. This potentiality was tackled in recent years, as the PCM parameters' applicability areas have been extended from monitoring purposes to trimming enhancements [5], yield prediction [6], yield detractors detection [7] or IC defect identification [8]. However, the PCMs are employed exclusively during the post-silicon (postSi) verification stage, where their number is much smaller compared to the productive dies measurements and IC issues (yield problems, defects, etc) have already appeared and caused production delays and money waste.

The Verification for Manufacturability by Modelling Process Variation - Circuit Performance Dependency **P2P4M** methodology [1] takes into consideration all these elements and models the relationship between IC's performances (under the form of Electrical Parameters - EPs) and the process variation (reflected by the PCMs), in a mathematical form by means of Machine Learning (ML) algorithms. The novelty consists in capturing this dependence during the pre-silicon stage, based on Monte Carlo (MC) co-simulations of the IC and PCM structure schematics. To the best of our knowledge, the P2P4M methodology is the only available tool to determine this mathematical relation during the pre-silicon verification. The **P2P4M** methodology has been successfully applied to parametric yield prediction [1], global and local sensitivity analysis with process variation [1], [9] and pre-silicon yield estimation [10].

However, the ML algorithms are stochastic algorithms, since there is an uncertainty degree involved in their learning and optimization processes or because they operate in stochastic domains [11]. This element of randomness may conflict with the careful inspection of the IC to ensure that they have been produced in accordance with the their specifications. Therefore, any methodology used in the IC development phase (as is the case of the **P2P4M** methodology) must be certified as robust and consistent, besides reaching the required high standards.

The goal of this research is to propose a robustness assessment plan for the **P2P4M** methodology, in order to perform a comprehensive evaluation with regards to the methodology functioning. Moreover, a special attention is paid to the case of operating across datasets for the same IC product. The rest of the paper is organized as follows: Section 2 presents a short description and the particularities of the **P2P4M** methodology employed in this research, followed by the proposed approach for the methodology robustness assessment provided in Section 3. Section 4 sums up the experimental results, while the conclusions are presented in Section 5.

2. The P2P4M Methodology

The Verification for Manufacturability by Modelling Process Variation - Circuit Performance Dependency **P2P4M** methodology, previously introduced in [1], is able to express an optimal relationship between each EP and the PCMs. The novelty of this approach stands in the fact that we address the modeling of the circuit performance behavior based on technology process variation for IC products that do not have dedicated PCM structures for every chip (which reflects the case for most of the products). The data availability issue is overcome by employing pre-silicon simulations, obtained by co-simulating the circuit and PCM structures schematics based on the methodology described in [12]. This leads to the estimation of the dependence of the device performances with the influential technology parameters very early in the development phase.

Fig. 1 depicts the schematic representation of the **P2P4M** methodology utilized in this paper. The ultimate goal is to obtain the optimal regression model, i.e. *metamodel*, associated to each EP, based on the available set of PCM parameters. Therefore, the input dataset is initially split into training and test datasets based on a random sampling of the overall distribution.

Each electrical performance of an IC depends on a limited and most of the times unknown set of technology parameters. In order to determine the precise set of PCMs exerting an influence on the studied EP, a feature selection step is used. This way, only the PCM parameters displaying a clear correlation with the EP under study with respect to a threshold are included in the *metamodel* training. For this, we used (Brownian) Distance Correlation - *DistCorr* $\Re(X, Y)$, a metric that quantifies the degree of independence between two variable and displays several advantages, out of which we mention: noise robustness, low computational cost and the ability to capture non-linear relationship between the variables [13]. The empirical sample $\Re_n^2(X, Y)$ is computed as follows:

$$\Re_n^2(X, Y) = \frac{\nu_n^2(X, Y)}{\sqrt{\nu_n^2(X)\nu_n^2(Y)}} \tag{1}$$

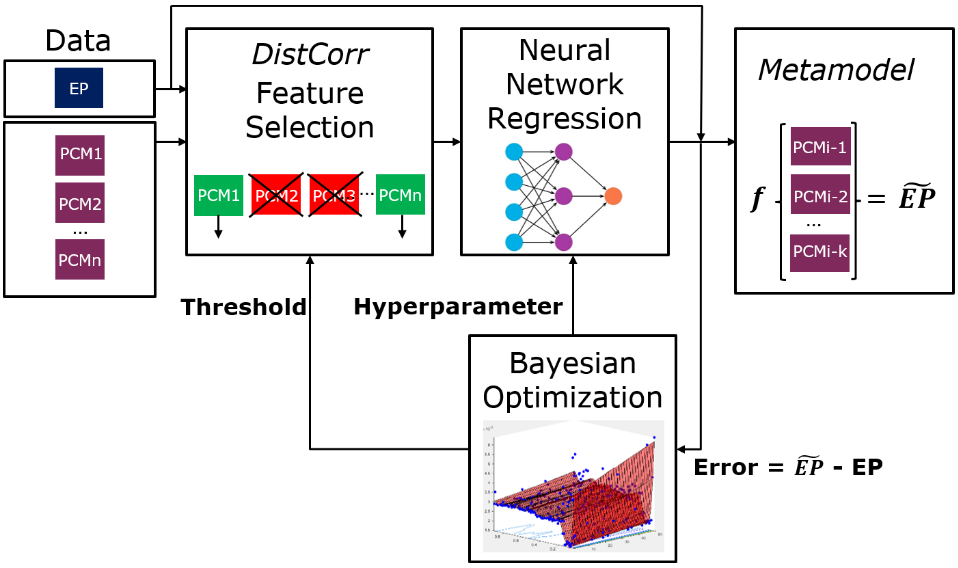

FIG. 1. The schematics of the **P2P4M** methodology employed in this research

where $\nu_n^2(X,Y)$ is the distance covariance, while $\nu_n^2(X) = \nu_n^2(X,X)$ and $\nu_n^2(Y) = \nu_n^2(Y,Y)$ are called distance variances.

Next, a multilayer perceptron (MLP) Neural Network (NN) prediction model is trained using the predetermined set of influential PCMs (as input) and the studied EP (as output), as it represents one of the fastest and most accurate regression solutions. The last two steps are wrapped up in the Bayesian Optimization (BO) framework, an optimization solution that iteratively samples in order to find the minimum of multi modal functions [14]. More precisely, two optimizable variables are declared - the threshold for *DistCorr* and the neurons number for NN and the above-mentioned steps are iterated for a specific number of times defined by the user. At each iteration, BO selects values for the two variables with the aim of minimizing the *metamodel* prediction error, a metric computed on the testing set; in this way, it adjusts the threshold and the number of neurons adaptively until it minimizes the test error function. Finally, the *metamodel* incorporating the functional dependence between the studied EP and its influential PCMs is obtained based on the optimal hyperparameters selected by BO.

3. The Proposed Approach for Robustness Assessment

The **P2P4M** methodology evaluation is performed based on several metrics, in order to support the previous discussion and report robust results. Firstly, the Mean Squared Prediction Error (*MSPE*) represents a metric that quantifies the quality of the *metamodel*, since it measures the squared distance between the prediction and the true values. Actually, the *MSPE* represents the cost function to- be-minimized by BO during the *metamodel* fitting.

$$MSPE = \frac{1}{n_{test}} \sum_{i=n_{train}+1}^{n_{train}+n_{test}} (EP_k^i - \widetilde{EP}_k^i)^2 \tag{2}$$

where n_{test} is the number of samples in the test dataset, that were not used in fitting the EP's *metamodel*, while n_{train} represents the number of samples in the train dataset. EP_{ki}^i and $\widetilde{EP}_k^i$ represent the actual and the predicted values of the EP_k, respectively.

Secondly, the *DistCorr* correlation coefficient computed between the studied EP and the available PCMs represents a methodology performance criterion. Even though the literature does not provide a certain threshold value to indicate the dependence between two variables, the **P2P4M** methodology set similar thresholds at several runs, which indicates a consistent behavior. Moreover, our experience based on a large set of extensive experiments conducted over the years, indicates that a 0.1 value of this metric reflects an observable dependence between two parameters instanced for minimum 500 times. Details on the computation formula are found in [13].

When discussing about the regression model accuracy (and implicitly of the **P2P4M** capability), it is important to decide if the ML algorithm was capable to extract the maximum information from the available data, i.e. there is no dependence between the residual error and the target. For this, another metric is introduced - the first-order correlation between the residual error and the target values of one EP $\rho_{\varepsilon-\mathrm{EP}}$, computed using Pearson's correlation, as seen in equation (3). Similarly, a reliable predictor maintains a high degree of correlation between the predicted and the true values. Therefore, the metric that assesses the correlation between the predicted and the target values of one EP ($\rho_{\widetilde{\mathrm{EP}}-\mathrm{EP}}$) is used, also defined based on first-order correlation, as it can be observed in equation (4).

$$\rho_{\varepsilon-\mathrm{EP}} = \frac{cov(\varepsilon_k, EP_k)}{\sigma_{\varepsilon_k}\sigma_{EP_k}} \tag{3}$$

$$\rho_{\widetilde{\mathrm{EP}}-\mathrm{EP}} = \frac{cov(EP_k, \widetilde{EP}_k)}{\sigma_{EP_k}\sigma_{\widetilde{EP}_k}} \tag{4}$$

It must be highlighted that *cov* and σ represent the covariance and the standard deviation, respectively, while $\widetilde{EP}_k$ are the predicted values of EP_k using the corresponding *metamodel* and EP_k are the target (real) values of the same parameter. Last but not least, $\varepsilon_k = EP_k - \widetilde{EP}_k$ is the residual error.

The available space on a wafer is narrow and consequently the PCMs structures and the PCM parameters monitored during production are limited. This is the reason why usually the monitoring is technology-oriented. Being able to precisely identify the technology parameters whose variation would affect the EP's behavior and transform the process into a product-oriented, translates into a better monitoring and the possibility to see a snapshot of the process variation at any time. Therefore, since we focus on providing a tool with an efficient functioning across datasets, during several iterations, another relevant aspect to be taken into consideration is the number and the selected subset of influential PCMs - $\mathbf{PCM}_i$. The P2P4M methodology should maintain its consistency during several iterations and identify the same set of influential PCMs when provided the same input.

4. **Experimental Results**

In order to experimentally assess the **P2P4M** methodology's reliability and consistency, we used two datasets from an Infineon Technologies low dropout voltage regulator (LDO). The main goal was evaluating the methodology's functioning capability across datasets. First, the experiments aimed to test the **P2P4M** methodology's coherence in providing the same results when being employed several times. Secondly, the methodology was applied on an extended PCMs dataset of the IC under study, most of them not monitored during the production phase, with the purpose of identifying other important influential PCMs. It should be mentioned that the considered EPs are typical LDO's measurable electrical performances and some of them are describing the same property under different operating conditions; the PCMs cannot be disclosed in this paper.

To conduct the proposed experiments, MC simulations have been obtained by co-simulating a setup that contained both the circuit model and the PCM structure schematics. The simulation structure displays the advantage of being able to reflect the changes determined in the same time by the process variation in both EPs and PCMs. Thus, the analysis was conducted on 32 EPs and two different datasets of PCMs - $initialSet93$ and $extendedSet198$, each one containing $N = 962$ samples. The $initialSet93$ included 93 PCMs, all of them being simulated during preSi and measured in the postSi phase on a regular basis. The $extendedSet198$ contained, besides the $initialSet93$, 105 additional PCMs that were not being monitored during the postSi production. Further, the dataset will be referred to as follows: PCM_k, with $k = [1, ..., 93]$ indicates an PCM parameter part of the initial set, while for $k = [94, ..., 198]$, the PCM is part of the $extendedSet198$.

The datasets underwent a pre-processing phase, consisting in normalizing the values in the [-1, 1] interval, as both PCMs and EPs (whether we are referring to the $initialSet93$ or to the $extendedSet198$) span across different orders of magnitude. Next, the entire dataset is split into training and testing sets - $n_{train} = 862$ and $n_{test} = 100$. This way, the reported metrics of the trained *metamodels*' accuracy are robust, since they refer specific to the testing dataset.

The **P2P4M** methodology was applied on the described datasets, during a four-iteration analysis, in order to provide sufficient variability, but keep the computational effort at reasonable costs. As presented in the previous subsection, five metrics have been considered for the analysis, namely: *MSPE*, *DistCorr* threshold, $\rho_{\widetilde{\mathrm{EP}}-\mathrm{EP}}$, $\rho_{\epsilon-\mathrm{EP}}$ and the number, as well as the subset of influential PCMs - $\mathbf{PCM}_i$.

In Figs. 2, 3 and 4 is illustrated the performance of the **P2P4M** methodology on three EPs, i.e. EP_1, EP_2, EP_3. It must be highlighted that these EPs are expressing the same electrical characteristic, i.e. current limitation, for different output voltage levels. It is easily noticeable that there are very small changes between the obtained metrics' results for all four runs, as well as for both PCMs datasets. The small values of the *MSPE* (around 0.018), together with the high correlation between the predicted and the target values (greater than 0.9) and the insignificant correlation between the fitting error and the real EPs (around 0.02) prove that the *metamodels* are reliable and accurate. In addition, the **P2P4M** methodology selected the same six influential PCMs $\mathbf{PCM}_i$ affecting the three EPs, thus confirming the methodology consistency and the fitting approach for the presented issue.

The following examples aim to prove that monitoring the proper PCMs for each product, instead of defining them based on the employed technology, brings several advantages to the semiconductor production stage. In Fig. 5 the performance of the **P2P4M** methodology for EP_7 is depicted. For this EP, the methodology chose 10 influential PCMs for 3 out of the 4 iterations. During

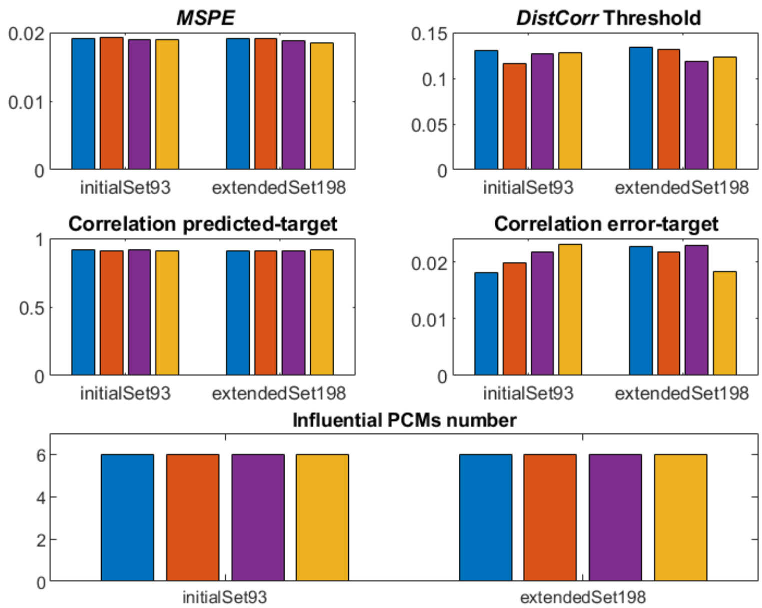

FIG. 2. The reliability and consistency results of **P2P4M**'s 4 runs for EP_1 (current limitation at V_{Q1})

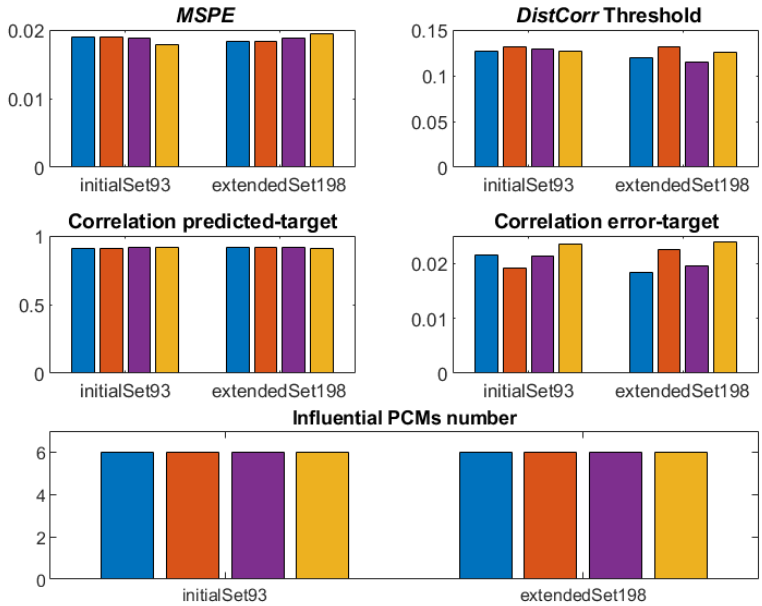

FIG. 3. The reliability and consistency results of **P2P4M**'s 4 runs for EP_2 (current limitation at V_{Q2})

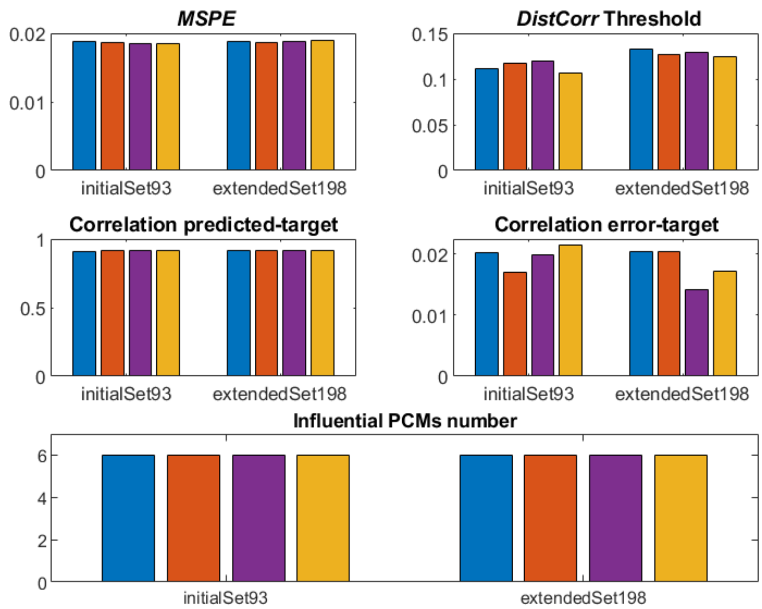

FIG. 4. The reliability and consistency results of **P2P4M**'s 4 runs for EP_3 (current limitation at V_{Q3})

run 3, PCM_{30} was put aside by the methodology through a slight increased value of the *DistCorr* metric (0.11). It leads to a marginally increase of the

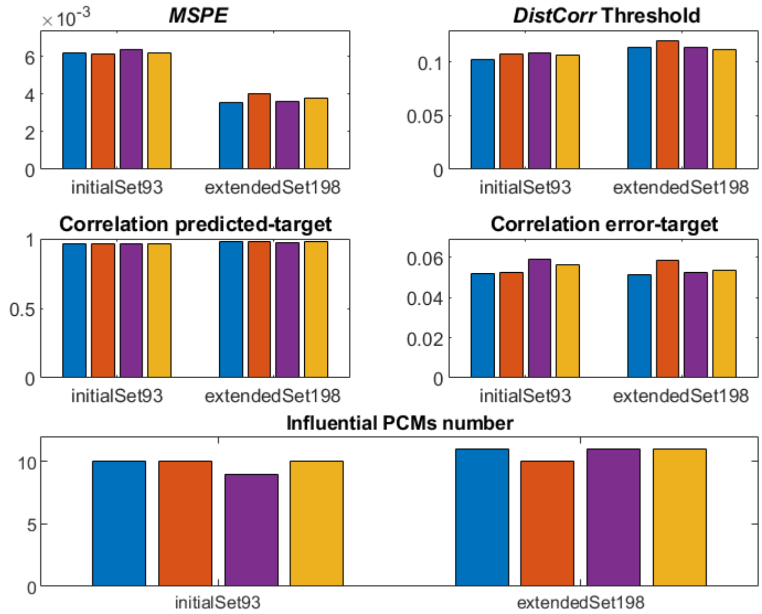

FIG. 5. The reliability and consistency results of **P2P4M**'s 4 runs for EP_7

MSPE value up to 0.0064, given the weak correlation between EP_7 and PCM_{30}. We can conclude that PCM_{30} displays a light influence on the studied EP and removing it from the set of influential PCMs does not appear to decrease the correlation between the predicted and the target values for EP_7, as the metric remains around 0.96 for all iterations.

In contrast, a clear improvement is obtained by applying the methodology on the extended dataset of PCMs (*extendedSet*198). Firstly, the *meta-models*' accuracy increases, as the *MSPE* average value is halved. Secondly, the number of influential PCMs oscillates between 10 and 11, even with an increase of the *DistCorr* threshold (up to 0.12). This is due to the current array of $\mathbf{PCM}_i$; when employing the *extendedSet*198, the **P2P4M** methodology chose two additional influential PCMs. These PCMs identified as PCM_{136} and PCM_{176} proved to be significant in explaining the EP_7's behavior. Moreover, benefiting from an extensive dataset of PCMs, the methodology removed from the influential PCMs list the PCM displaying the weakest correlation with the studied EP, namely PCM_{30}.

These conclusions are enhanced by the color-coded portrayal of the *DisCorr* correlation coefficients between the extended set of PCMs and EP_7, illustrated in Fig. 6. It should be recalled that the *initialSet*93 includes the PCMs' indexes from 1 to 93, while the rest until index 198 represent the extra PCMs that are only preSi simulated in the presented analysis. Two PCMs from the *initialSet*93 - PCM_{56} and PCM_{57} are highly influencing the EP_7,

TABLE 1. **The influential PCMs selected by P2P4M for EP_7 out of the *initialSet93* and *extendedSet198***

Parameter	Influential PCMs - PCM_i	
	initialSet93	***extendedSet198***
EP_7	$PCM_{36}, PCM_{37}, PCM_{53}, PCM_{56}, PCM_{57}, PCM_{79}, PCM_{80}, PCM_{81}, PCM_{82}$	PCM_{136}, PCM_{176}

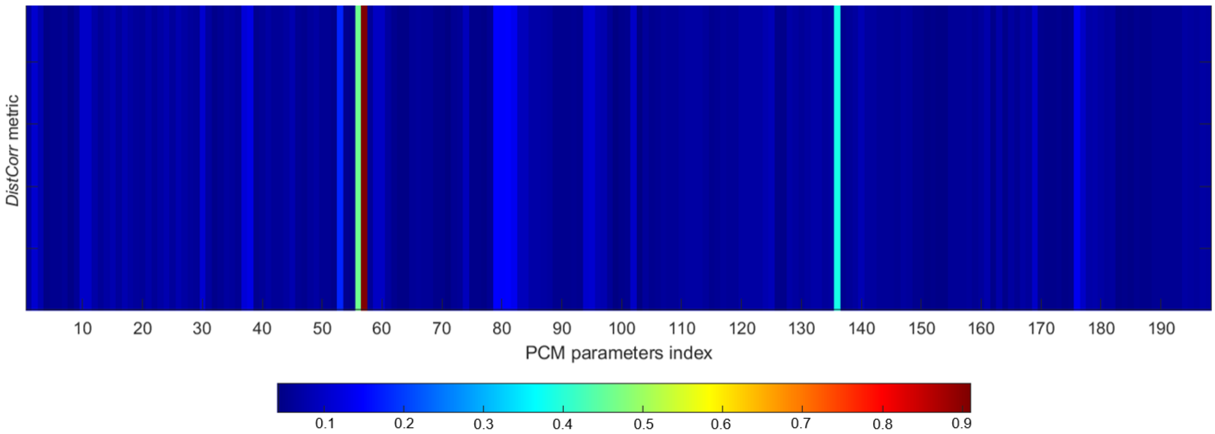

FIG. 6. *DistCorr* metric values between EP_7 and all of the available PCMs in the study (*extendedSet*198)

with *DistCorr* scores of 0.4602 and 0.9098, respectively. These two PCMs are among the influential PCMs identified by the **P2P4M** methodology.

Table 1 presents the entire set of influential PCMs; besides to above-mentioned PCMs, the methodology was able to correctly select several other PCMs in order to provide the optimal *metamodel*. The remaining seven influential PCMs display weaker correlations with EP_7, around 0.2-0.3 and they are represented with light blue in the Fig. 6. Out of the *extendedSet*198's PCMs, PCM_{136} surpasses the rest of 105 additional PCMs, displaying a *DistCorr* correlation coefficient equal to 0.3860.

Continuing on the same note, the following example highlights the significant influence of the extended PCMs' dataset on the performance of the **P2P4M** methodology. Fig. 7 illustrates the methodology's performance for EP_{11} and one can easily conclude that the results obtained by using the smaller dataset represents an explicit example of EP's behavior that is poorly explained by the available PCM parameters. The resulted *metamodels* display low accuracy, as their *MSPE* revolves around 0.12, even for the *DistCorr* threshold

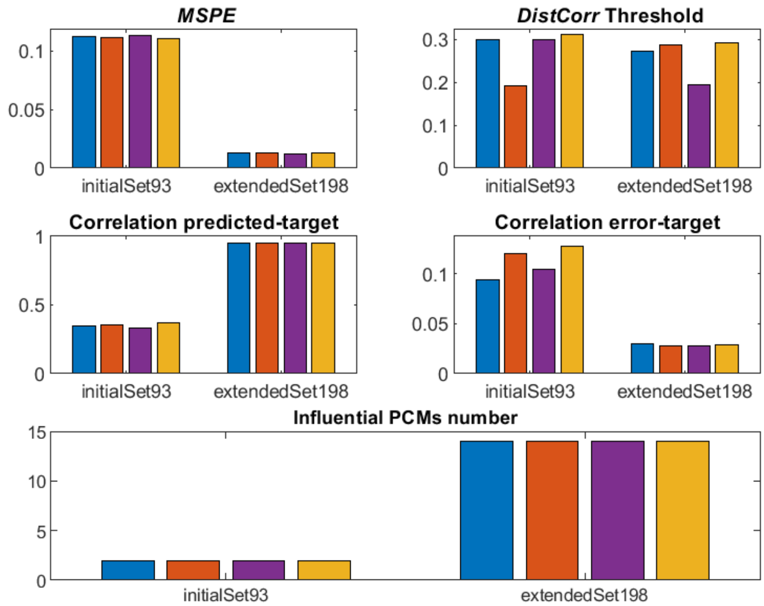

FIG. 7. The reliability and consistency results of **P2P4M**'s 4 runs for EP_{11}

taking values between 0.19 and 0.31. In the same time, the correlation between the predicted and the target values of the EP is smaller than 0.35, since the **P2P4M** methodology was able to select only two influential PCMS. These PCMs identified as PCM_2 and PCM_{30} display a significant correlation with EP_{11}, as their *DistCorr* correlation metrics are 0.3468 and 0.3259, respectively. Yet, this proves not to be sufficient to reasonably describe EP_{11} and the P2P4M methodology is able to return the best *metamodels*, given the insufficient set of *initialSet*93 PCM parameters.

When applying the methodology on the *extentedSet*198, a certain improvement to the *metamodels*' accuracy is obtained. Despite the fact that the average value of the *DistCorr* threshold actually decreased compared to the case of the *initialSet*93, the average *MSPE* decreased to 0.02 and the Pearson's correlation between the target and the predicted increased to 0.97. This improvement is due exclusively to the extended set of PCMs on which the accurate and optimal *metamodels* were trained. The last plot from the Fig. exhibits a set of 14 PCMs that clearly influence the EP_{11}'s behavior.

In Table 2, the entire set of influential PCMs is presented. As previously stated, only two PCMs from the initial set are involved in the analysis, followed by 12 additional PCMs from the extended set. The PCMs having indexes from 189 to 193 display the highest correlation with EP_{11} and Fig. 8 helps supporting this statement.

The highest *DistCorr* correlation coefficients are obtained for PCMs that are not currently monitored during the production phase and it represents

TABLE 2. **The influential PCMs selected by P2P4M for $\mathbf{EP_{11}}$ out of the *initialSet93* and *extendedSet198***

Parameter	**Influential PCMs - $\mathbf{PCM}_i$**	
	initialSet93	***extendedSet198***
EP_{11}	PCM_2, PCM_{30}	$PCM_{94}, PCM_{95}, PCM_{102}, PCM_{110}, PCM_{111}, PCM_{120}, PCM_{121}, PCM_{189}, PCM_{190}, PCM_{191}, PCM_{192}, PCM_{193}$

a clear weakness for the manufacturing process. The maximum *DistCorr* value reaches 0.6983 and it is almost double the maximum correlation metric obtained between EP_{11} and the *initialSet*93's PCMs. Consequently, the relationship between the optimal enhanced *metamodels* and the use of the *extentedSet*198 becomes straightforward, as the influence of the 12 PCMs chosen from the additional 105 PCMs is critical when explaining EP_{11}.

Besides the five highly correlated PCMs (depicted with red), the other seven PCMs (enumerated in Table 1) display a comparable correlation to the influential PCMs selected by the methodology from the initial set (at least 0.3). It is clear that the entire set of 12 influential PCMs from the extended dataset should definitely be monitored during the postSi production phase by the technologist, because even the smallest deviation in these parameters will modify EP_{11}'s behavior.

The remaining 27 EPs displayed similar behaviors as the 5 presented in this sub-section, ranging from the same results, to slight improvements or

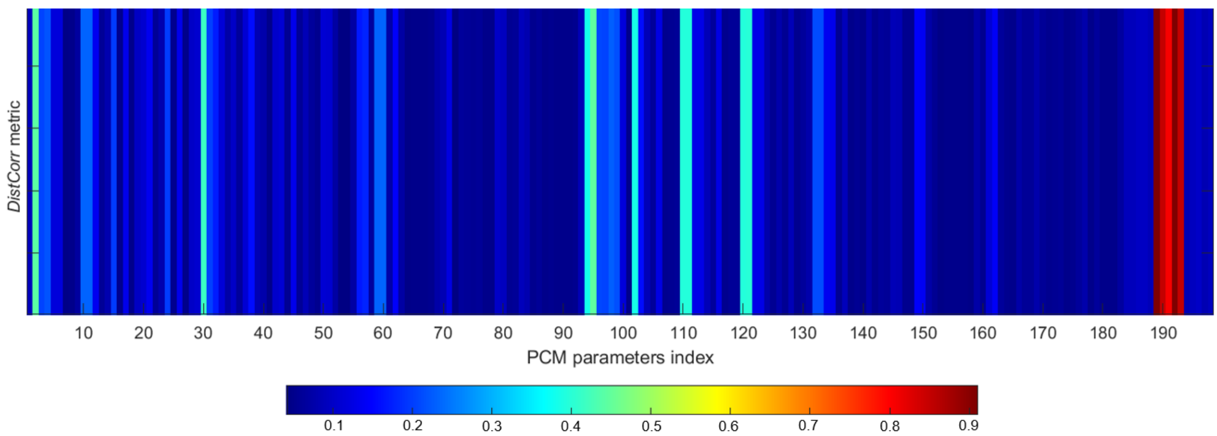

FIG. 8. *DistCorr* metric values between EP_{11} and all of the available PCMs in the study (*extendedSet*198)

significant improvement obtained when applying the **P2P4M** methodology on the $initialset93$ and $extendedSet198$, respectively.

5. Conclusions

The predominantly strong dependence between IC performances and the process variation (expressed through the PCMs) has been revealed and modelled with the help of the **P2P4M** methodology. Nevertheless, ensuring a reliable and consistent solution for an industry governed by imperative safety measures, as is the case of the semiconductor production, represents a crucial measure. Therefore, the paper performs an extended analysis on the **P2P4M** methodology, in terms of reliability and consistency, given the stochastic nature of the employed ML algorithms.

The experimental results confirms that the **P2P4M** methodology is coherent at different runs, by maintaining the accuracy metrics variation in acceptable limits while returning the same subset of influential PCMs ($\mathbf{PCM}_i$) for the same initial set of PCMs. It passed the consistency and reliability tests, proving to be an efficient tool for the designer.

Moreover, the **P2P4M** methodology highlighted that there are PCM parameters that have a clear impact on the EPs, but they are not monitored in production (only simulated in pre-silicon). No decrease in performance was reported when employing the $extentedSet198$, so the best trade-off should be found for every IC product in what concerns minimizing the space required for the PCM structures and defining the PCMs to maximize the monitoring information. This way, the methodology becomes a valuable tool for the technologist as well.

In addition, besides the confirmation provided by the experimental results obtained on the available data, our conclusions were validated by the circuit designer, as well as the technologist. Future research efforts should be directed towards monitoring the newly discovered influencing PCMs in post-silicon, followed by a reiteration of the analysis on the acquired post-Silicon data, to increase the reliability of using solely pre-silicon data.

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