WHITE PAPER

How to faster calculate information generated by a production machine?

Introduction

Majority of machine producers think that they know all about their machines. Ask for example Toyota car producers and they will claim that nobody in the world knows better their technology. But how did it happen then that they made production mistakes which have shaken their empire to the bottom and caused deep apologies? They simply stick to a model of failures in production that is scientifically known as statistical entropy measure. What is wrong with this model? It simply states that you have to wait statistically long enough for the mistake to manifest itself in order to measure it. This fact is well measured with Shannon's information theory. What do you think, how long should your clients wait until the mistake manifests itself? A year, a week or just a few hours? We claim that under all other circumstances unchanged, our approach to entropy calculation on your machine can generate the proper information on a possible error orders of magnitude faster. Our approach is based on an information measure named: expanded Carnap entropy. By using this approach, one can spare in decreased fallout in ceramic tile production line or achieve better QC control in machine production.

Machine and information

One should follow the existing data set available for your machine. Thus, in an experiment setting, we had 204 measurements taken from five presses at the KIO Keramika ceramic tile plant in Orahovica, Croatia. One to three measurements were taken in each working day depending on the number of shifts. The 37 relevant measured production signals included: tile humidity signal (no. 10), pressing tool temperature signals (upper matrix, lower matrix, press frame and press oil temperatures) (no. 11-14), thickness between the press frames signals (no. 16-20), thickness over the press frames signals (no. 21-25), skewness between the press frames signals (no. 26-30), skewness over the press frames signals (no. 31-35), tile firmness signals (no. 36-40), and furnace temperature signals (no. 44-51).

The goal was to model quality control variable (labeled QC), expressed as percentage of rejected tiles (fallout) per daily shift. We had to determine which signals influence the quality of the final product the most and in which time periods in order to enable preventive actions as soon as possible.

Sequencing the information

All the data were sequenced in four serial measurements, as depicted in Fig. 1. The changes between measurements were taken as a ternary code basis. Thus we obtained 27 codes. The interdependencies among these codes were expanded, thus obtaining the matrix form for two codes, as in Fig. 2.

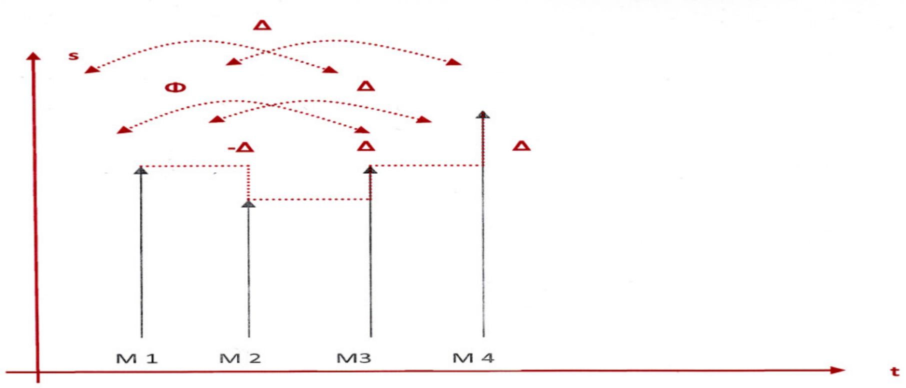

Fig. 1. Sequence of four measurements

$$I^{M(-++)} = \begin{bmatrix} -\Delta & \Delta & \Delta \\ - & 0 & \Delta \\ - & - & \Delta \end{bmatrix}$$
$$I^{M(+--)} = \begin{bmatrix} \Delta & -\Delta & -\Delta \\ - & 0 & -\Delta \\ - & - & -\Delta \end{bmatrix}$$

Fig. 2. Fully expanded matrices for code (-++) and (+--)

Calculating the information content

Generally, any measurement signal can be presented as a *Δ*-modulated signal, which is a signal composed of a series of unit step changes. This signal approximation can be used as a basic approximation of the quality control signals.

Putting the form from Fig. 1 into a one-dimensional case yields:

$$I_C^{1D} = -\sum_{i=1}^{k} \frac{|d_i|}{x_k} \log_2 \frac{|d_i|}{x_k} \qquad \text{(bit/V)},$$

where $|d_i|$ is distance that individual points x_i cover, see Fig. 3 for example of $k = 4$.

By putting the six differences from the matrix in Fig. 2 into such a 1-D graph one can obtain a unique information measure of the four point measurement sequence.

Control of the machine performance

We put all the codes from machine signals in a table form together with shift time scale. This form, which is named *impactogram*, can be labeled with three marks: for dissimilar code, for identical code, but different Carnap entropy content, and with identical code and identical Carnap entropy content.

We present an example of exact impactogram interpretation for press #9 in KIO Orahovica ceramic tile plant. Impactogram is depicted in Fig. 4. Impactogram locations that have different ternary codes form the QC signal are shown in white (code „0“), those with the same codes, but different Carnap entropy are grey (code „1“), and those with equal codes and entropies are shown as dark grey (code „2“). Relevant measurement occurrences are also marked with frames and thus separated from irrelevant measurements.

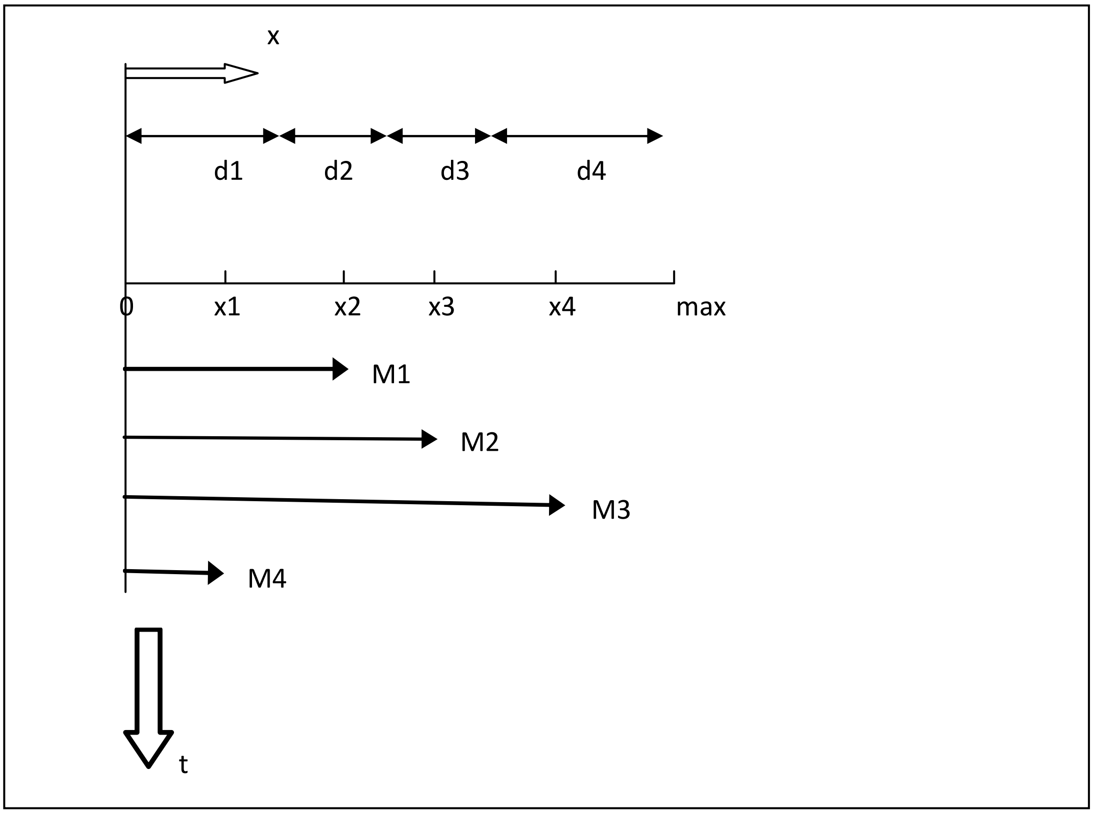

Fig. 3. One-dimensional Carnap information of the four point measurement sequence

Relevant measurement occurrences include time intervals $\lambda = \{27, 28, 29, 30\}$. We provide interpretation for a case of critical QC variable value at measurement occurrence no. 30 in press #9 (QC=7.41% rejected tiles). The following signals are relevant in these measurement occurrences as

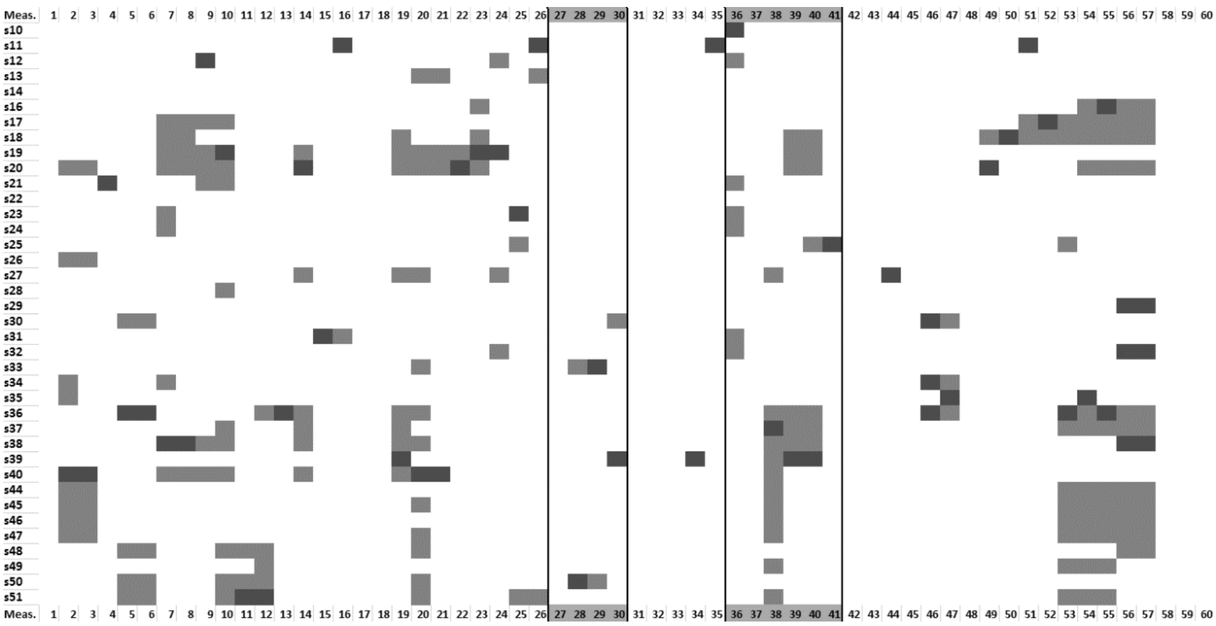

Fig. 4. Impactogram of the press #9 and QC data, sequences with production losses above 7% are indicated in frames

seen from impactogram: $\gamma(s_{33}, 28) = "1"$, $\gamma(s_{50}, 28) = "2"$, $\gamma(s_{33}, 29) = "2"$, $\gamma(s_{50}, 29) = "1"$, $\gamma(s_{30}, 30) = "1"$, $\gamma(s_{39}, 30) = "2"$. Entropy in $j = 28$ equals: $I_{33}^{28} = 1.792, I_{50}^{28} = 1.545, I_{QC}^{28} = 1.569$. Therefore, signal s_{50} (increased furnace temperature) is the most probable cause of the defect. Signal s_{33} has a larger entropy difference from QC and is not a probable cause of additional failure.

Conclusion

A simple, fast and low-demand computing method for measurable information enquiry in automated batch production system was shown. This data variability method is based on the one-dimensional expanded Carnap entropy concept, which takes control signal as four-by-four point samples from the process and calculates its information content. We have shown that this information measure can be applied to automated production process by interpreting the analysis of impacts that process signals have on the QC variable. The interpretation is useful for finding causes and effects of interesting QC events. Finding out which signals caused the event and what were the effects in the automated production cycle is an important step in preventing such events in the future by eventually changing machine settings. The presented method will benefit control and QC engineers in applying tools for the unique follow-up of process quality dynamics in cases where the exception to the quality standards sporadically occurs.

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