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Fault diagnosis of an industrial plant using a Monte Carlo analysis coupled with systematic troubleshooting

Irina Boiarkina [a], Nick Depree [a], Wei Yu [a], David I. Wilson [b], Brent R. Young [a,*]

[a] Industrial Information and Control Centre, Chemical and Materials Engineering, University of Auckland, 2-6 Park Ave, Grafton, Auckland 1023, New Zealand

[b] Auckland University of Technology, School of Engineering, Computing & Mathematical Sciences, Auckland 1142, New Zealand

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A B S T R A C T

Efficiently troubleshooting a fortification issue at an industrial milk powder plant is a complex undertaking given the myriad of possible causes. Multiple causes, even when simple, are not easy to diagnose, however every single cause needs to be addressed in order to consistently meet product quality specifications. This paper uses statistical modelling in the form of Monte Carlo simulations to investigate the probable causes for unexpected excessive product variation. This approach alone, refines but does not completely solve, the production issues, so a systematic approach was required to definitively solve other root causes. This two-step fault diagnosis approach ensured that all of the differing causes proposed by plant personnel could be addressed, and sound recommendations for good manufacturing operations could be made and adopted.

1. Introduction

Many processing industries have recently seen a shift away from maximising production with process control to a focus on quality, and process analytical technology (PAT) has come to stand for the assessment and control of product quality. The popularity of PAT was partly due to the strong FDA encouragement in the US pharmaceutical industry (FDA, 2004), but since has spread to other manufacturing industries (Munir, Yu, Young, & Wilson, 2015). The international dairy company Fonterra Co-operative Group Ltd, the world's largest fluid milk processor, has recently been looking to accelerate the development and use of PAT tools to achieve ‘real time quality’ (RTQ), combining the benefits of advanced process control (APC) with an explicit focus on quality (Hunter et al., 2012; Munir et al., 2015; Rimpiläinen, Kaipio, Depree, Young, & Wilson, 2015).

The attractions of real time quality are obvious. If one is confident that the product currently being manufactured is to specification, then savings can be made on off-line subsequent testing, while simultaneously minimising the possibility of producing significant amounts of off-spec product that must be recycled or rejected. However the development of appropriate tools to achieve this requires that one understands the nature of the underlying quality issue in order to carry out the appropriate corrective action. From an analysis of historical poor quality events, it was decided that this work would concentrate on the timely identification and subsequent correction of faults. Whilst seemingly simple, practical fault diagnosis on large interconnected plants is complicated. There is a natural human bias to search for a single phenomenological cause, as opposed to multiple, single failures, which is often unwarranted.

Standard techniques for industrial fault diagnosis and monitoring can be found in Gertler (1998) and Chiang, Russell, and Braatz (2001), those employing simple rule-based methods such as expert systems (Rich & Venkatasubramanian, 1987; Zahedi, Saba, Al Otaibi, & Mohd-Yusof, 2011), or dynamic process modelling (Bertanza, Pedrazzani, Manili, & Menoni, 2013), or even data driven multi-variate methods such as principal components analysis (PCA) and multi-variate data analysis (Eslamloueyan, 2011; Li, Alcala, Qin, & Zhou, 2011; Qin, 2012; Ralston, DePuy, & Graham, 2001; Singhal & Seborg, 2006). It may be prudent to distinguish between

* Corresponding author.
E-mail addresses: i.boiarkina@auckland.ac.nz (I. Boiarkina), n.depree@auckland.ac.nz (N. Depree), w.yu@auckland.ac.nz (W. Yu), diwilson@aut.ac.nz (D.I. Wilson), b.young@auckland.ac.nz (B.R. Young).

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methodologies applied to a simulated process, such as the benchmark Tennessee Eastman plant (Chiang et al., 2001; Gertler, 1998; Lee, 2004; Yin, Ding, Haghani, Hao, & Zhang, 2012), those applied at a pilot plant scale (Ruiz, Maria Nougues, & Puigjaner, 2001), and those applied on an actual industrial plant (Bertanza et al., 2013; Ge, Chen, & Song, 2011; Ralston et al., 2001; Zahedi et al., 2011). The latter often contain subtleties that are important to the overall success of the programme.

When looking at it from the industrial point of view the method depends on its appropriateness to the end goal and the information available. Possible aims include:

1. Find general problems across the entire plant. This may include standard equipment failures or abnormal operation. Data driven methods such as PCA and MVDA are appropriate here as they capture a large quantity of information simultaneously and are non-specific. However these techniques require knowing a 'normal' mode of operation, which is not always easily established.
2. Troubleshoot a specific problem. The causes may be singular or multiple and varied. Expert systems can be of some help here, as troubleshooting a specific issue may require knowledge specific to the process to explain it adequately. A dynamic model of the process for elucidating the exact cause, such as that used by Bertanza et al. (2013) when troubleshooting a wastewater treatment plant. General data processing methods can also be applied although they will result in black box models, such as PCA, that may be difficult to interpret.

1.1. An application of fault diagnosis in the dairy industry

This work considers an industrial milk powder plant where the product is fortified with specific ingredients in minute and carefully controlled quantities to the customer specification. However one of the added ingredients showed larger than expected concentration variations in the final product, with below-specification results.

Initially it was unclear whether the variation was a fault, or a natural consequence from the normal processing. This uncertainty precluded the use of some data driven processing methods that require the identification of a 'normal' operating state, such as PCA. However a model of the fortification process could be used to establish whether the variation and below-specification results were probable or not, based on the variation of the inputs. This was combined with a Monte Carlo (MC) strategy of running simulations of the process model repeatedly and comparing with the available quality data, which was measured infrequently and difficult to trace back to the process conditions.

Goldfeld and Dubi (1987) reviewed the use of the Monte Carlo method for reliability engineering within the manufacturing industry and an application of the Monte Carlo method for analysing manufacturing failures in electronic components is reported by Accumolli (1996). In this latter case it was used to estimate the percentage of the final product that could be expected to fail, as the final product could not be tested. In both cases the failure causes were already known, and neither work looked at using the Monte Carlo method specifically for troubleshooting.

Monte Carlo for uncertainty analysis has also been used for understanding penicillin V production by Biwer, Griffith, and Cooney (2005) and for analysing the uncertainty around wastewater treatment plant models by Sin, Gernaey, Neumann, van Loosdrecht, and Gujer (2009). However, again both of these works look at the uncertainty propagating through the process. For penicillin production it was used for assessing the resulting variability in the economics and environmental performance of the process, whilst for the wastewater treatment it was used for design modelling. Thus, the aim in both cases was not to troubleshoot and evaluate whether the variation was normal for the process or not. This troubleshooting aim is a novel aspect of this work.

Where the broad Monte Carlo strategy was found to be ineffective, a case-by-case approach followed, made far more manageable by the reduction in the fault search-space by the broader approach used initially. This ensured that all aspects of the problem could be covered. This requires domain specific knowledge. For example, the troubleshooting of a distillation column requires case-by-case evaluation of possible column malfunction causes (Kister, 2014; Kister, Stupin, Lenferink, & Stupin, 2007). Similar case-by-case approaches can be taken for other operations such as pneumatic conveying and filter operation (Mills, 2016; Sparks & Chase, 2016). However, analysing each failure individually can be time consuming when each one can have multiple route causes, therefore having a broad technique to eliminate as many of the potential causes as possible before carrying out a case-by-case analysis is very useful.

During this fault diagnosis, we noted themes that could be generalised to troubleshooting at any industrial plant. We found that plant personnel had differing pre-conceived notions on the root causes of the problem and this meant that during the fault diagnosis the approach taken had to resolve the differences in opinion in order for any proposed solutions to be adopted at the plant. Using the Monte Carlo uncertainty analysis followed by individual analyses was effective at uncovering both single phenomenological and multiple single simple causes and capturing the quality issue holistically.

The outline of this work is as follows. Section 2.1 describes the specific industrial problem used as a case study and lists the competing solution hypotheses. To resolve which potential problem was indeed the root cause, a Monte Carlo analysis was undertaken in Section 2.2. However the statistical analysis alone could not resolve all the potential causes, so a systematic cases-by case analysis was used in Section 3.5 and both strategies resulted in concrete operational changes outlined in Section 3.6. Finally a generalisation of this specific case study illustrating how it can be applied in other instances is given in Section 4.

2. Theory

2.1. Fault description

Milk powder is typically fortified during processing by the addition of several ingredients. These ingredients are normally added to the evaporator flow using a dedicated dosing system, as shown in Fig. 1.

The dosing system consists of two tanks, one for dosing and one for making up fresh solution of the ingredient to be ready for switch-over as shown in the inset in Fig. 1. The target (denoted by an asterisk superscript) solid mass of ingredient to be diluted for dosing can be calculated using a mass balance based on the mass of solids going through the evaporators in the milk, and the target concentration in the final milk powder (specified by the customer). The final milk powder is composed of the ingredient, the milk solids and a small amount of left over water. Using a mass balance approach, the target solid mass of ingredient to dissolve, $m_I^\star$ (kg), is,

$$m_I^\star = \frac{C^\star \, V^\star \, q_E \, x_s}{q_D \, (1 - x_m)(1 - L)} \tag{1}$$

where $C^\star$ is the target milk powder ingredient concentration (mg/g milk powder), $V^\star$ is the target fill volume of the dosing tank used