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Simplification of Data Acquisition in Process Integration Retrofit of a Milk Powder Production Facility

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Process integration techniques, such as Pinch Analysis, can be used to effectively detect energy saving opportunities in the industrial sector. However, their application is mainly limited to energy-intensive processes, leaving a large potential untapped in the remaining industrial sectors. One factor that discourages the application of these tools is the requirement of a large amount of reliable data, which may be difficult or time-consuming to gather. This paper presents the application of a method to simplify the data acquisition step of process integration studies on a milk powder production facility. By employing uncertainty analysis and sensitivity analysis techniques, the solution of the factor fixing problem was shown, and a subset of parameters whose accurate estimates were essential to obtain reliable analysis results, were detected. The required data reduction was significant, as only 20 out of the 41 parameters initially considered were deemed to be important. Moreover, the maximum acceptable level of inaccuracy in the definition of these parameters in order to ensure a satisfactory uncertainty level in the analysis output was presented. The output standard deviation was reduced from the initial 47.8 % to 10.0 %, relative to the mean value.

1. Introduction

Process integration (PI) techniques have been shown to be effective in identifying energy saving opportunities in several industrial sectors (Kemp, 2007). However, despite their proficiency, they are rarely utilized and far from constituting the common industrial practice. This is especially true for non-energy intensive industries, which are often reluctant in investing in energy analyses and energy saving measures (Kimura et al., 2015) because of the significant time demand (order of weeks) and financial investment required to collect all required measurements and process data (Klemeš and Varbanov, 2010). Few authors tried to address this issue by acknowledging data acquisition as a critical step in PI studies. Muller et al. (2007) proposed to first apply a top-down approach to identify the major energy users based on energy bills, followed by a bottom-up one used for the detailed modeling of the simplified process. The validity of the method was illustrated by a case study, but a large amount of data was still required, as a thorough characterization of the most consuming sections of the plant was necessary. Pouransari et al. (2014) showed that it is possible to retrieve data at different detail levels without compromising the validity of the conclusions drawn by a PI analysis. However, they did not propose criteria able to identify the required detail level beforehand. Kantor et al. (2018) developed a method for constructing thermal profiles of specific processes based on a database of generic sub-process data. This method is still in the development stage, and its accuracy for representing operation of entire plants is yet to be proven. Finally, a list of generic issues encountered in the data acquisition step of PI analysis and advice for its successful completion was presented by Klemeš and Varbanov (2010).
This paper presents the application of a recently developed data acquisition simplification method (Bergamini et al., 2019) on a dairy facility producing milk powder. Based on roughly estimated process data, uncertainty analysis and sensitivity analysis were used to identify the parameters (e.g. temperature, flow rates) that have minor impact on the final results and their uncertainties. This problem, named the *factor fixing problem* (Saltelli et al., 2008), aims at determining the parameters that can, therefore, be fixed to any value in their uncertainty range and can be overlooked during the detailed data acquisition phase.

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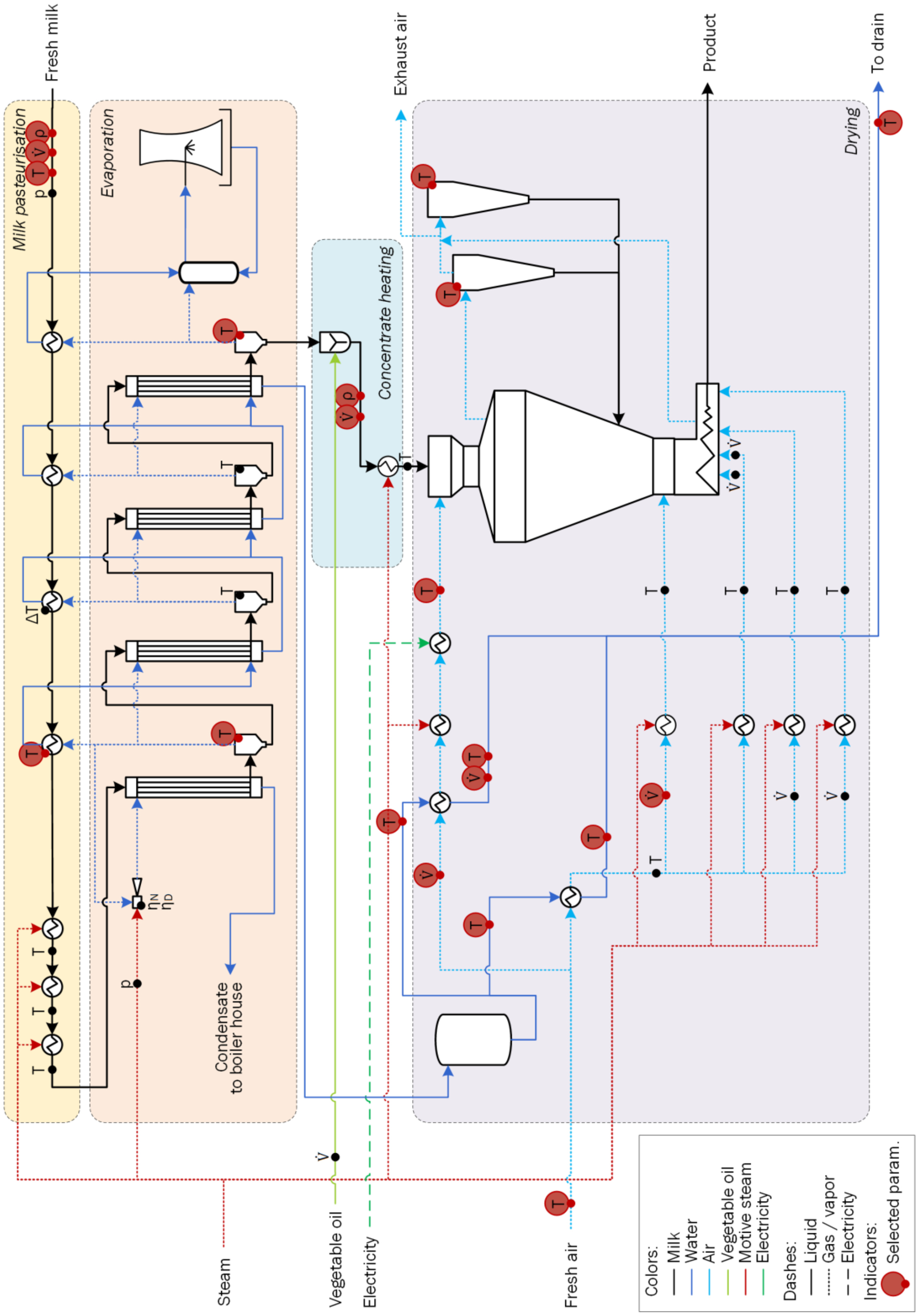

Figure 1: Case study process layout, parameter positions and resulting sensitive parameters (circled in red)

Moreover, the applied method identifies the precision with which the influencing parameters need to be acquired in order to achieve satisfactorily reliable results in the energy targeting procedure of Pinch Analysis. In this way, the analyst is provided with a tool that is able to systematically identify the important parameters to be measured and the precision with which this operation should be performed. All this is done before allocating time in collecting a large number of possibly important data.

2. Method

2.1 Process description and modeling

The analyzed process is from a milk powder production facility located in northern Europe. The process flowsheet is presented in Figure 1. The powder production rate at full capacity is estimated to be 4,500 kg/h, corresponding to a heating demand of around 4,000 kW, presently supplied mainly by steam. The production line consists of four sub-processes: (i) milk pasteurization, (ii) evaporation, (iv) concentrate heating and (iv) drying. Fresh milk with 13 % Total Solids (TS) content enters the line at around 6 °C and is heated up to 90 °C using seven steam heaters in series. It is then concentrated to around 50 % TS across a four-stage evaporation line equipped with Thermal Vapor Recompression. After being re-heated to 75 °C, it undergoes the final drying step in a spray dryer where it is dried up to around 97 % TS, and it is then sent to packaging. Some degree of process integration is already implemented, as a share of the heat available in the warm condensate leaving the evaporator is used to preheat the fresh air supplied to the spray dryer. Cooling towers are used to satisfy most of the cooling demand, required by the remaining condensate cooling from the evaporators.
The process was modeled based on process flow diagrams. It included mass and energy balances for the 24 components in the plant. No possibilities for modifying the existing separation system were considered of interest, and hence the evaporation line and the spray dryer were assumed to have a fixed configuration. 41 parameters were identified as necessary for describing the system from an energy perspective (Figure 1). Out of these 41 parameters, 34 were measured, consisting of (i) 21 temperature, (ii) 9 volume flow rate, (iii) 1 density. The remaining 10 parameters were assumed from knowledge provided by the plant operators and designers. They consisted of (i) 4 temperature, (ii) 1 volume flow rate, (iii) 1 density, (iv) 2 pressure, and (v) 2 component performance data. Finally, physical system constraints were implemented in the model to ensure process consistency under uncertain input parameters (e.g. the saturation temperature of an evaporation stage cannot exceed the one of upstream stages). The model was coded in MATLAB® (‘MATLAB Release R2017b’, 2017).

2.2 Pinch Analysis data acquisition simplification strategy

The data acquisition simplification procedure proposed by (Bergamini et al., 2019) was applied to the case study. It aims at reducing the time consumption in the data acquisition step of process integration studies by employing uncertainty analysis and sensitivity analysis concepts to the well-known Pinch Analysis targeting procedure (Kemp, 2007). The applied procedure consisted of four main steps:

1. *Rough data acquisition.* A model of the system was built by identifying the required input parameters. Four outputs were defined as important, namely: (i) minimum hot utility consumption (HU_{min}), (ii) minimum cold utility consumption (CU_{min}), (iii) energy saving potential (E_{save}), and (iv) actual plant hot utility consumption (HU_{actual}). The first two outputs resulted from the pinch energy targeting procedure, the latter output was retrieved from the process model, and the third was calculated as the difference between (i) and (iv). The input parameters were thereafter characterized by assigning estimated values retrieved by the plant monitoring system during the same production day for most parameters, while the rest were assumed based on expert consultation.
2. *Uncertainty analysis.* Input uncertainties were defined (see Section 2.3 for further details) and an uncertainty analysis was performed on the model in order to estimate output uncertainties based on the rough data acquisition. A Monte Carlo analysis (Metropolis and Ulam, 1949) with sample dimension of N=1,000 was employed in this study. A maximum acceptable target uncertainty was defined for each output as 10 % of its nominal value. This served for defining the maximum acceptable uncertainty (Step 4) in data retrieved during the detailed data acquisition.
3. *Sensitivity analysis.* A variance decomposition-based sensitivity analysis was performed to solve the factor fixing problem (Saltelli et al., 2008). The total sensitivity index (S_{Ti}) referred to each output was calculated for each parameter and considered for sensitivity definition (Saltelli et al., 2009). It univocally identifies all the contributions (first and higher orders) of the *i*-th parameter to the output variance. A number of simulations N = 60,000 was used.
   A sensitivity threshold was set equal to S_{Ti} = 0.01 and the parameters with lower impact were disregarded for the detailed data acquisition step of the retrofit analysis.
4. *Allowed uncertainty maximization.* By means of a global optimization routine, the input uncertainties of the parameters selected in Step 3 were maximized to meet the maximum acceptable output uncertainty defined in Step 2. This served as an indication of the level of accuracy required in the detailed data acquisition step

and, possibly, it further reduces the number of parameters to consider for retrieving data that are more precise. The lower bound definition for the input uncertainty is explained in Section 2.3.

2.3 Input uncertainty definition

Input uncertainty characterization is crucial for obtaining meaningful results from the previously described method. This is far from trivial, as generally, various sources of uncertainty contribute to it, namely: (i) *knowledge uncertainty* deriving from inadequate information (comprising measurement uncertainty) and faulty assumptions, and (ii) *natural variability* resulting from process variations deviating from steady-state conditions (Loucks and van Beeck, 2017). Unfortunately, such uncertainties are not known a priori, particularly when only a rough data acquisition is performed (Step 1). Therefore, subjective evaluation must be made. For each parameter, three different uncertainties must be defined: (i) uncertainty relative to the rough data acquired in Step 1, (ii) minimum uncertainty, and (iii) maximum uncertainty obtainable when performing a detailed data acquisition (Step 4).

Input uncertainties were described by means of a normal distribution, according to the work of Madron (1992). The probability distribution was centered in the parameter nominal value (μ), while its standard deviation (σ) was assumed based on the type of parameter to be measured, distinguishing between (i) temperature, (ii) volume flow rate of liquid flow, (iii) volume flow rate of gaseous flow, (iv) density, and (v) other. The standard deviation of the roughly estimated parameters was set to high values according to what was recommended by Bergamini et al. (2019). The maximum standard deviation obtainable when performing a detailed data acquisition was set to the same value as the rough ones, corresponding to the situation in which no detailed data acquisition was performed. Finally, the minimum obtainable uncertainty was set according to the minimum inaccuracy of marketed measurement sensors, as reported by Liptak (2003). These were either defined as (i) absolute values (ABS), (ii) relative to reading (RE), or (iii) relative to Full Scale (FS). For the latter, the full scale of unknown sensors was assumed to be three times the read value. The adopted standard deviations are listed in Table 1.

Table 1: Parameter uncertainty definition

Parameter type	Rough data σ (reference)	Maximum σ (reference)	Minimum σ (reference)
Temperature	3 K (ABS)	3 K (ABS)	0.1 K (ABS)
Volume flow rate, liquid	10 % (RE)	10 % (RE)	0.1 % (RE)
Volume flow rate, gas	10 % (RE)	10 % (RE)	1 % (FS)
Density	10 % (RE)	10 % (RE)	1 kg/m^3 (ABS)
Others	10 % (RE)	10 % (RE)	1 % (RE)

3. Results and discussion

3.1 Uncertainty analysis

The uncertainty propagation by means of Monte Carlo analysis resulted, as expected, in high uncertainties, ranging from 8.5 % to 47.8 % of the output average value (Table 2). These values where well above the set limit of 10 %, hence a more detailed data acquisition was deemed necessary and the simplification procedure was continued.

3.2 Sensitivity analysis

Figure 2 presents, for each output, the total sensitivity indexes of the 41 parameters sorted in descending order. As it can be noted, a limited number of parameters was deemed influencing for the output variance, specifically: 7 parameters for HU_{min} (a), 10 parameters for CU_{min} (b), 17 parameters for E_{save} (c), and 6 parameters for HU_{actual} (d). Moreover, it is shown that for all the outputs the parameters S_{Ti} decreased rapidly in the first few parameters, while it flattened for the remaining ones. For all the outputs, the chosen cut-off threshold (shown in dashed line) was able to detect this flattening behavior. The resulting most influencing parameters for the four selected outputs was 20, which constitutes a significant decrease from the initial 41 parameters. The 20 most influencing parameters are highlighted with red circles in Figure 1. Referring to the maximum S_{Ti} calculated for each input,

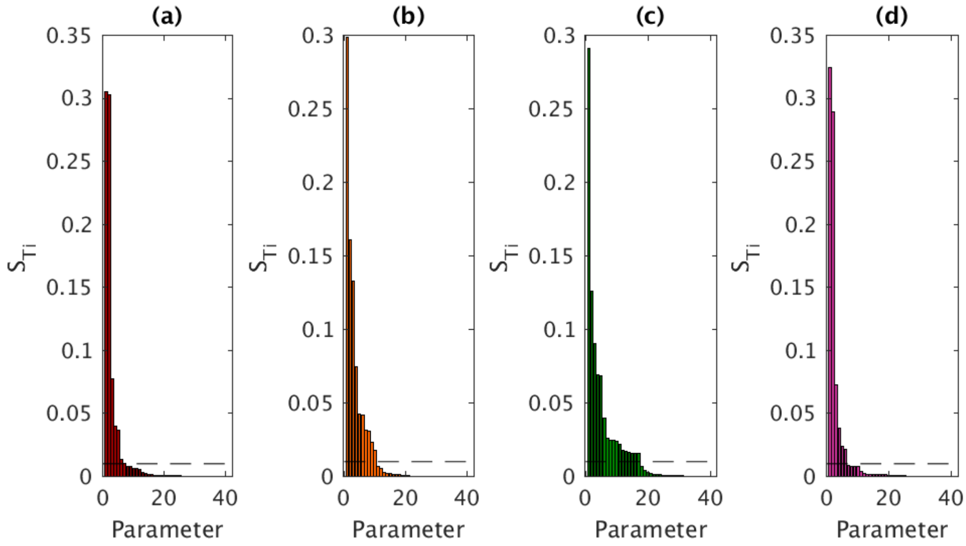

Figure 2: Total sensitivity index of the k = *41 parameters on the outputs, sorted in descending order. (a) HU_{min}, (b) CU_{min}, (c) E_{save}, (d) HU_{actual}*

precise measurements/estimates of the fresh milk and concentrate properties were observed fundamental (0.03 ≤ S_{Ti} ≤ 0.30) altogether to the temperature after the recuperative preheating stage (S_{Ti} = 0.13). Moreover, only the saturation temperatures of the first (S_{Ti} = 0.16) and last (S_{Ti} = 0.04) evaporation stages were important, concerning the evaporation section, while intermediate stages and ejector parameters resulted to be of secondary importance. Concerning the spray dryer, inlet (S_{Ti} = 0.29) and outlet (S_{Ti} = 0.07) air temperatures were of concern, while only volume flow rate (S_{Ti} = 0.32) and temperature (S_{Ti} = 0.01) of the main air stream and volume flow rate (S_{Ti} = 0.02) of the static fluid bed airflow were identified as relevant. The rest of the stream properties did not have a significant impact on the results precision. Finally, temperature (S_{Ti} = 0.02) and flow rate (S_{Ti} = 0.02) of the condensate heat recovery system resulted to be fundamental to determine the actual energy savings potential accurately. These values, in particular, were not monitored with precision in the plant, as they are not paramount for controlling the plant production. On the contrary, this analysis shows that their careful monitoring would be beneficial when the plant energy performance is of interest.

3.3 Allowed uncertainty maximization

At first, the uncertainty analysis was repeated, setting the uncertainty of the selected 20 parameters to their lower limit and keeping the rest to the initial values. This identified the potential minimum uncertainty achievable by precisely monitoring all the selected parameters. The results (Table 2) showed that the output uncertainty would be significantly reduced in this case, falling below the minimum requirement of 10 %. Thereafter, the required parameter uncertainty was maximized in order to reach the necessary 10 % output accuracy. The resulting final uncertainty is presented in Table 2, while the parameters uncertainty reduction required with respect to the rough data uncertainty is shown in Figure 3. From the latter it is clear how not all the 20 selected parameters needed to be assessed with extremely high precision. On the contrary, 7 of them (parameter 10, 12, 13, 16, 17, 18, 19 in the figure) required only a slight uncertainty reduction. This shows the possibility to allow a little increase in output uncertainty in order to overlook these parameters in the detailed data acquisition phase, in addition to the ones selected in Step 3 of the procedure. This would further reduce the number of important parameters to 13.

Table 2: Output uncertainty calculation, using (a) rough data, (b) minimum uncertainty on the 20 selected parameters, (c) maximized uncertainty on the 20 selected parameters

Output	(a)		(b)		(c)	
	Absolute	Relative to μ	Absolute	Relative to μ	Absolute	Relative to μ
HU_{min}	279 kW	8.72 %	59 kW	1.83 %	80 kW	2.49 %
CU_{min}	257 kW	47.80 %	33 kW	6.13 %	54 kW	10.00 %
HU_{actual}	83 kW	14.56 %	16 kW	2.77 %	47 kW	8.33 %
E_{save}	321 kW	8.50 %	67 kW	1.77 %	87 kW	2.30 %

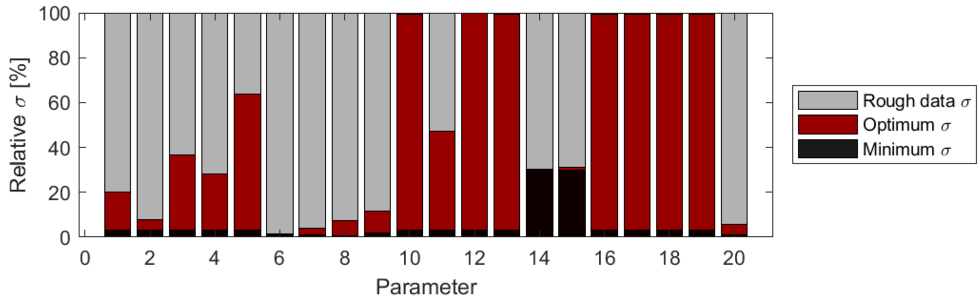

Figure 3: Target parameters uncertainty, relative to the initially estimated values, for the 20 selected parameters

4. Conclusions

This paper presents the application of a recently developed data simplification technique for process integration retrofit projects on a milk powder production plant. The method was shown to be able to reduce the number of parameters to be considered during the detailed data acquisition phase significantly by identifying 20 parameters of paramount importance out of the initial 41. This was achieved by applying a systematic procedure requiring only roughly estimated data to be performed, potentially achieving a significant reduction in time use during the data acquisition stage. In this way, the output standard deviation was reduced from the initial 47.8 % to the desired level of 10.0 %, relative to the mean value. Moreover, the method was shown to be able to identify the maximum allowed inaccuracy in the data acquisition on the reduced sub-set of parameters in order to achieve a required level of accuracy in the analysis outcome. The results suggested the possibility to further reduce the parameters of paramount importance to 13. This could serve as a reference for planning the measurement campaign to be performed in the detailed data acquisition phase, and for recommending the placement of permanent sensors aimed at improving the plant monitoring system. This possible use should be further investigated in future research, and the impact of the assumptions made in the uncertainty characterization should be assessed, establishing the robustness of the developed method.

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